WHAT IS THE FULL COST OF BODY MASS IN THE WORKPLACE?

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Abstract

MATT HARRIS: What is the Full Cost of Body Mass in the Workplace?
(Under the direction of Donna Gilleskie.)

This dissertation discusses results obtained by formulating and estimating a dynamic stochastic model of individuals' annual joint decisions of occupation, hours worked, and schooling. A standard dynamic occupational choice model is augmented by allowing body weight to affect the non-monetary costs and distribution of wages for each occupation. The model also captures the effects of individuals' employment decisions on body weight in subsequent periods through on-job activity levels, disposable income and time available for leisure. Conditional density estimation is used to model the stochastic evolution of body weight and formulate the distributions of wages in each occupation. I estimate the model using data from the National Longitudinal Survey of Youth, 1979 cohort, the Dictionary of Occupational Titles, and Occupational Information Network. Results suggest individuals with higher body weight are likely to incur wage penalties in occupations with intense social requirements. Further, individuals with excess body weight earn lower returns to experience and face greater switching costs in white-collar occupations than healthy weight individuals. Simulating the model with estimated parameters, I find that halving the weight-specific frictions in switching occupations reduces the gap in wages between the obese and non-obese by 12%. Further, an exogenous reduction in an individual's initial body mass by 10% leads to a 1.5% increase in wages over the life course, and increases the probability of attaining employment in professional occupations by 5%.

Acknowledgments

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Chapter 1

Introduction

Social scientists have become increasingly interested in the relationship between body weight and labor market outcomes as Americans have consistently gained weight over the past four decades. While there is a strong negative relationship between weight and income in the United States, debate in the economics literature continues on whether this relationship is causal or purely associative.[1] Unlike differences in wages along race or gender lines, which are often attributed to discrimination due to the exogeneity of these characteristics, the causes of weight-based differentials in wages and observed employment behavior are more complicated. First, one can argue that overweight individuals are not as well suited for some occupations and therefore should make less. Being overweight may interfere with job performance if that occupation requires physical skills such as agility. Additionally, if the populace regards overweight people as less appealing, heavier people may be less effective in socially intensive jobs (Averett and Korenman, 1996). Further, an individual's weight, which is largely a function of the individual's history of diet and physical activity choices, may provide a valid endogenous signal about that individual's self-discipline or work ethic. If the importance of this signal varies by occupation, it would not only create wage differentials that vary across occupations but also create barriers to certain occupations for higher body weight individuals. Such effects can lead to differences in occupational sorting between the healthy weight and overweight, subsequently affecting future wages. Finally, an individual's body weight is dynamic. Unlike race or gender, one's employment decisions may affect his body weight. Data on young males from the

[1] Among white men earning over four times the poverty level in 2004, 14% were obese. The obesity rate among white men near the poverty line was 24% (Baum and Ruhm, 2009).

National Longitudinal Survey of Youth suggest that, since 1983, the average difference in real wages between the obese and non-obese has tripled. Determining the relative importance of the above factors in this trend is the primary motivation for this dissertation.

The purpose of this work is to analyze the relationship between body weight and optimal employment behavior over the life of the individual. To that end, I formulate and estimate a dynamic discrete choice model where weight affects both the distribution of wage offers and non-monetary costs of each employment alternative, and employment decisions subsequently affect weight. I construct indices of the intensity of mental, physical and social job requirements for each occupation to assess whether observed weight-related differences in wages are attributable to differences in productivity. Additionally, this dissertation examines how weight affects individuals' costs of pursuing each combination of occupation/hours. The non-monetary costs of pursuing an alternative are sub-divided into three components: switching costs when changing occupations, annual fixed costs of pursuing an occupation, and the marginal costs of working additional hours. These costs are also linked to the indices of job requirements. Although lacking the data on employer preferences necessary for a general equilibrium framework, this parsing of the costs enables estimation of the lower bounds on the share of weight-driven differences in employment behavior attributable to worker and employer preferences.

This dissertation extends the literature in four ways. First, weight-related wage differentials are incorporated into the individual's dynamic optimization problem. Forward-looking agents evaluate employment alternatives mindful of expected future wages, returns to experience, and switching costs, all of which vary by weight. This dissertation estimates the importance of differences in endogenously accrued years of schooling and experience to the observed dispersion in wages on the basis of weight. I extend the literature on wage penalties for body weight that has abstracted from the importance of experience and only examined occupational selection in a static framework (Cawley, 2004; Pagan and Davila, 1997; Johar and Katayama, 2012; Hamermesh and Biddle, 1994).

A second contribution is the model's ability to assess how much of the observed differences in wages and employment decisions between individuals of different weights are due to the requirements of the job. Using job requirement data from the Dictionary of Occupational Titles

(DOT) and the Occupational Information Network (O*NET) and CPS weights, I construct novel indexes of the mental, social, and physical requirements of each aggregated occupational alternative in each time period. In evaluating how wage penalties for weight vary with the intensity of requirements, I extend the research that suggests that weight penalties occur in occupations with higher social demands (Averett and Korenman, 1996). Previous work has not evaluated the effects of mental or physical rigors of occupations on wage penalties for body mass.

Third, this dissertation extends the literature on how an individual's employment behavior affects his weight (King et al., 2001; Lakdawalla and Philipson, 2002; Kelly et al., 2011; Courtemanche, 2009). In addition to the inclusion of the time-varying job requirements, I also allow the unobserved shocks that affect weight gain and choice of occupation and hours to be serially correlated through a common permanent unobserved component. By including exogenous environmental factors and capturing how utility from each employment alternative changes as one ages and gains weight, my model alleviates simultaneity and selection biases while quantifying the role of the employment decision on body weight over the life cycle.

Finally, the model is solved using techniques common in structural dynamic discrete choice modeling (Keane and Wolpin, 1994; Sullivan, 2010). To more flexibly model the distribution of wages and body weight over time, I use a semiparametric method, conditional density estimation (Gilleskie and Mroz, 2004). For the purpose of modeling individuals' expectations, this technique enables the estimation of any moment of the conditional distribution of wages and body weight without any distributional assumptions on those variables. I incorporate permanent unobserved heterogeneity in a nonparametric fashion into the wage expression, costs of employment alternatives, and weight process (Heckman and Singer, 1984; Mroz, 1999)

To evaluate the effect of an individual's weight on his optimal employment behavior, I use the dynamic model and estimated parameters to simulate annual employment and schooling decisions from ages 17 to 47 under different counterfactual scenarios. Results indicate that differences in endogenously accrued occupational experience account for approximately 10% of the growth in wage differences between the obese and non-obese over the sample period. Changes in job requirements over the sample period account for an additional 17% of the growth in wage differences between the obese and non-obese from 1983-2008. I find that unobserved heterogeneity plays a large role in the dynamic relationship between body weight and occupational choice. Simulating the model with estimated parameters, I find that a policy intervention that would halve the weight-specific frictions in switching occupations reduced the gap in wages between the obese and non-obese by 5%. Further, an exogenous reduction in an individual's initial body mass by 10% leads to a 1.5% increase in wages over the life course, and increases the probability of attaining employment in professional occupations by 5%. An exogeous shock to weight delivered mid-career has a more pronounced effect. An exogenous shock of a one 'weight-class' (Five BMI points) at age 35 leads to an expected 6% gain in wages and 5% greater likelihood of participating in white collar occupations.

This dissertation proceeds as follows. Chapter 2 provides a brief motivation and background on the relationships between body weight and employment outcomes. Chapter 3 describes the relevant data: the National Longitudinal Study of Youth, 1979 cohort, the DOT, O*NET and the ACCRA cost of living index. Chapter 4 details the dynamic model to be estimated. Chapter 6 discusses identification and the empirical implementation of the theoretical model. Chapter 6 contains the parameter results and discusses how the model predicts the variation of interest in the data. Chapter 7 contains counterfactual simulation using the estimated paraeters of the model, and Chapter 8 concludes with a brief discussion of the results contained herein and discusses possible extensions and areas for further research.

Chapter 2

Background

Reported costs of obesity, generally, result from medical care utilization, adverse health outcomes, and mortality. However, excess body weight also carries significant costs in the workplace. Lost productivity due to obesity amounts to $12 billion annually (Ricci and Chee, 2005). Only one third of this estimated cost is attributed to absenteeism. Reduced presenteeism, or lost productive time at work, accounts for the remainder. The value of that time is measured by observed or predicted wage of workers. Obese workers were 16% more likely to report lost productive time and 14% more lost hours than their healthy peers due to fatigue, lack of focus, or health considerations. In a second study, effort in the workplace was positively associated with cardiovascular fitness, but obesity was the largest contributing factor to poor management of interpersonal relationship in the workplace (Pronk et al., 2004). The economics literature provides supporting evidence for the negative relationship between body weight and productivity by linking higher body weight to lower earnings for white women. For white men, the significance of the estimated wage penalty depends on whether unobserved individual heterogeneity, which may affect both weight and wages, is addressed (Cawley, 2004; Pagan and Davila, 1997; Averett and Korenman, 1996; Baum et al., 2006). The economics literature also suggests that in occupations with heavier social requirements (e.g., salesman, lawyer) overweight or obese individuals earn less on average than their peers (Johar and Katayama, 2012; Hamermesh and Biddle, 1994; DeBeaumont, 2009). If higher body weight causes individuals to earn less than their healthy weight peers, then estimates of lost productivity due to obesity based on observed wages are low. Conversely, if unobserved heterogeneity drives both the propensity to gain weight and the tendency to be idle or disengaged in the workplace, than the above estimates of productivity losses are overstated.

Productivity, conditional on education and work experience, may not be the sole cause of wage differentials between individuals with observable differences (i.e., gender, race, weight). The economics literature posits three possible explanations for observed wage gaps: differences in productivity, taste-based discrimination, and statistical discrimination (Altonji and Pierret, 2001; Levi-Gayle and Golan, 2012; Farber and Gibbons, 1996). One can identify statistical discrimination as the explanation if the wages of the initially-discriminated group increase with experience (relative to those who entered employment with higher initial wages). My own preliminary regressions do not provide evidence of statistical discrimination against overweight or obese individuals relative to those of normal weight.[1] Taste based discrimination is more difficult to identify, and may be indistinguishable from differences in productivity without exceptionally rich data. Recognizing this difficulty, the partial equilibrium framework in this dissertation includes time-varying indices of physical, mental, and social requirements of each occupation in an effort to link observed wage differentials to productivity. As such, this work provides a lower bound on the share of the measured wage differential attributable to productivity.

Differences in human capital may explain differences in wages. In this dissertation, per the standard in the economics literature, human capital is defined as years of schooling and accrued work experience. If heavier individuals face higher costs in gaining employment or attaining a desired occupation, an individual's weight in a given period may affect his accrual of human capital and thus affect future wages. Severe obesity has been a protected category under the Americans with Disabilities Act (ADA) since a 1993 Rhode Island ruling barring employment bias against obese people. Judge Bruce Selya stated in his ruling, "In a society that all too often confuses 'slim' with 'beautiful' or 'good', obesity can present formidable barriers to employment." In the last two years, the Equal Employment Opportunity Commission (EEOC) has claimed that obesity is a disability in and of itself, filing suits in Louisiana, Texas, and New York on behalf of employees who claimed they faced weight-based discrimination. A hospital in suburban Houston, Texas recently instituted an explicit ban on the hiring of employees who

[1] Regression output and tables of differences will be made available shortly in a web appendix of supplementary supporting evidence from the data.

were at least moderately obese. Pagan and Davila (1997) find some evidence of occupational sorting on the basis of weight. They find that obese white males incur wage penalties in some occupations. Further, they observe that the obese are found in occupations without weight-related wage penalties in greater proportions than their healthy weight counterparts. It was not determined if this difference in employment behavior between obese and non-obese workers are attributable to weight-related wage penalties, barriers to employment, or individual heterogeneity. Examining wages from a dynamic perspective increases the relative importance of endogenous differences in occupational sorting on the basis of weight. Not only does an individual's choice of occupation affect his wages this period, but it affects his expected future wages as well. Experience in blue-collar, white-collar, and service jobs are not equally rewarded in subsequent periods. Most previous economic research on the relationship between weight and income has focused on the effects of individuals' weights on their wages, utilized static methods, and abstracted from modeling occupational choice.[2]

In this dissertation, estimation of the parameters of an individual's dynamic optimization problem enables me to allocate shares of the observed weight-related differences in observed wages to endogenous differences in experience and years of schooling, differences in productivity as defined by job requirements, and to unobserved heterogeneity. I allow serially correlated (permanent) unobserved heterogeneity to affect wage distributions, costs of employment alternatives, and weight gain. Remaining differences in wages explained by variation in body weight are considered unbiased weight-based wage penalties.

In addition to measuring the effect of weight on wages, this research seeks to quantify the role of wages, worker preferences, and job requirements as explanations for observed differences in employment behavior by weight status. As childhood and adolescent obesity continues to increase, the generation currently entering the workforce is the heaviest yet. Understanding the complex relationship between weight, productivity, wages and optimal employment behavior has become increasingly important. If individuals with higher body weights are ill-equipped to perform certain occupations, then the motivation for interventions to combat adolescent and

[2]Notable exceptions to the lack of dynamic modeling include Gilleskie, Norton, and Han (2011) and Tosini (2008), but neither study models occupational choice.

adult obesity intensifies. Using the model and estimated parameters, I simulate the effects of changes in individuals' initial weights on their employment profiles over their life cycle. However, if individuals with higher body weight face obstacles to occupational attainment beyond those attributable to the requirements of the occupation, then vigorous pursuit of anti-discrimination initiatives on the basis of weight may have implications for social mobility, as adolescent obesity is a worse problem in low income families and neighborhoods. Such a hypothetical policy can be simulated using the estimated parameters of the model.

While data limitations prevent me from exploring the role of employer preferences as an explanation of occupational sorting patterns by weight, the estimated partial equilibrium model provides a lower bound of the impact of worker utility and employer preferences. For example, Hamermesh and Biddle (1994) pose that the clientele of employers may have preferences for conducting business with attractive people. Therefore, overweight individuals should face greater difficulty attaining work in occupations with heavy social requirements. Further, by modeling the choice of hours worked jointly with occupation, one can observe the optimal extensive and intensive margin of labor supplied by individuals of different weights. In this manner, I can estimate a lower bound on the differences in utility from each employment alternative attributable to body weight. Finally, with those factors captured, I can estimate any additional frictions faced by individuals of higher body weight in transitioning between occupations.

The associative relationship between occupational choice/employment behavior and weight change does not adequately address selection effects and unobserved heterogeneity that may explain why heavier individuals tend to sort into different jobs than their healthy weight counterparts. (King et al., 2001; Lakdawalla and Philipson, 2002; Kelly et al., 2011; Courtemanche, 2009). As such, it is difficult to quantify the role of hours worked and job characteristics on life-cycle weight transitions. By modeling the decision of occupation and hours worked, I can recover unbiased indirect effects of these decisions on weight gain over time. I can re-assess whether longer hours worked or reduced on-job physical activity causally influence weight gain without selection or simultaneity bias.

Chapter 3

Data

The data for estimating this model come from three sources. The data on individuals' wages, employment decisions, body mass, environments, and family states are from the National Longitudinal Survey of Youth, 1979 cohort (NLSY '79). Data on job requirements comes from the Dictionary of Occupational Titles (DOT) and its successor, the Occupational Information Network (O*NET). Regional data on food prices come from the 4th quarter reports from ACCRA (formerly the Inter-City Cost of Living Index).

The NLSY '79, conducted by the Bureau of Labor Statistics, follows a nationally representative cohort of youths initially aged 14-22 annually from 1979 to 1994 and biennially to 2010.[1] Respondents were asked questions regarding family background, schooling, occupation, hours of work, wages, criminal activity, health, etc. Weight data are recorded for 1981, 1982, and in each wave since 1985. For the purpose of this study, the main limitation of the data is that information on food and exercise decisions was not collected until the last two waves. However, the NLSY '79 is the longest running nationally representative panel which contains data on weight, wages, and employment decisions. To construct the sample used in estimation, I drop all individuals lost to attrition, those who miss an interview, and restrict the focus to white males. I restrict the sample to white males to keep an already heavily parameterized model computationally feasible. Including females and other races would require parameters for demograhpic shifters on all variables of interest. I remove those who miss interviews for the sake of computation time. In the empirical implementation of the model (see Chapter 5),

[1] http:\\www.nlsinfo.org

Calculating choice probabilities for individuals who miss interviews requires integration over the distribution of uncaptured work experience due to unobserved employment decisions. This represents a significant additional computational burden. The inclusion of individuals who attrit also would impose additional computational burdens as it would require additional solutions to the model (see section 5.7). More than half of those who attrited from the sample missed also missed at least one interview prior to permanent attrition. Table 3.1 explains the sample construction. The final sample consists of 29,693 person-year observations. Descriptive statistics for the full sample (12,686) persons and full demographic subsample (4,699) are available in table 3.2 and demonstrate that the sample used for estimation (1291) and full sample are similar along observables.

Table 3.1: Sample Construction

N	**Description**
12,686	National Longitudinal Survey of Youth, 1979 cohort, full sample
3,720	Sample after restricting demographics to white males
2,566	Sample after restricting sample to nationally representative, civilian group
1,978	Sample after dropping all individuals who attrit
1,291	Sample after dropping those individuals missing an interview

1291 unique individuals yields 29,693 person/year observations

Source: National Longitudinal Survey of Youth, 1979 cohort

Individuals' reported occupations are classified according to their Census Occupation Codes. In order to construct and estimate a tractable discrete choice model, I aggregate those occupations into the five major categories from the 1970 Census Occupational Classification System.[2] Table 3.3 lists the five occupation categories used in this research and displays how proportions of selected occupations have changed over time in the sample.

[2] As the NLSY progressed, the occupation classification system was updated for the 1980 census (in 1983) and the 2000 census (in 2002). Where necessary, I used BLS-provided crosswalks to convert more recent occupation codes to the coarser 1970 SOC classification.

Table 3.2: Summary Statistics- Full v. Working Sample of 1979 NLSY

	Working Sample		Full Sample	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Age	17.368	2.251	17.898	2.306
Yrs. Ed.'79	10.412	2.825	10.333	2.712
Weight	144.496	29.692	145.500	29.697
Yrs. Ed '98	13.521	5.567	13.021	4.988
Income 79	17818.878	13179.965	14777.898	12495.053
Income 98	27144.634	26835.683	25518.661	26527.117
# of Kids	0.339	0.713	0.376	0.738

Occupation class proportions, 1981		
Variable	Working Sample	Full Sample
No Work	0.455	0.510
Professionals	0.057	0.053
Sales & Admin	0.164	0.148
Craftsmen	0.050	0.049
Laborers	0.131	0.116
Service	0.144	0.124
N	1,291	3,720

Table 3.3: Observed Frequencies of Occupational Alternatives

Occupation	1984-1989	1990-1998	2000-2008
Not Employed, Not in School	10.47%	6.83%	11.59%
Professionals, Technicals, Managers	22.16%	33.71%	36.73%
Salesmen, Clerks, Administrators	13.89%	11.44%	9.07%
Craftsmen	18.76%	19.79%	17.98%
Operators & Laborers	24.87%	20.85%	16.76%
Service Workers	10.01%	7.38 %	7.88%
N	9,960	11,620	6,640

Individuals in the sample range from ages 14 -22 in 1979.

Table 3.4: Fixed Effect Regression of Wages on Experience, Obesity, and Family Variables

	Occupation 1: Professionals Technicals Managers		Occupation 2: Administrative Clerical and Sales		Occupation 3: Craftsmen (Skilled) Blue		Occupation 4: Operatives and Laborers		Occupation 5: Service Workers	
Variable	**Coef.**	**(S. E.)**	**Coef.**	**(S. E.)**	**Coef.**	**(S. E.)**	**Coef.**	**(S. E.)**	**Coef.**	**(S. E.)**
Obese	**-113.22**	(44.06)	**-124.68**	(50.73)	-14.87	(27.20)	-34.07	(26.59)	25.46	(52.25)
H.S.	-78.62	(122.93)	33.60	(38.68)	34.48	(48.42)	**69.79**	(24.36)	-3.78	(28.44)
College	**190.40**	(55.06)	**307.66**	(60.01)	**229.75**	(80.94)	**133.71**	(49.01)	103.57	(63.11)
Experience (Occ. 1)	**52.74**	(11.26)	**53.79**	(14.01)	18.21	(20.38)	**18.38**	(8.39)	21.34	(11.30)
Experience (Occ. 2)	**45.36**	(16.14)	**64.31**	(14.26)	1.56	(18.44)	3.17	(8.31)	**62.49**	(21.94)
Experience (Occ. 3)	**-27.53**	(14.00)	**42.46**	(21.72)	10.93	(8.70)	8.46	(6.34)	9.96	(17.83)
Experience (Occ. 4)	**-71.38**	(16.61)	-14.91	(16.00)	-5.37	(10.15)	5.83	(4.09)	19.59	(12.25)
Experience (Occ. 5)	-5.72	(20.85)	13.66	(27.82)	11.12	(20.26)	-15.69	(9.75)	**26.83**	(8.14)
Married	**66.72**	(25.01)	**96.75**	(38.23)	**73.38**	(17.81)	**56.58**	(12.69)	**52.77**	(27.82)
No. of Kids	**99.02**	(22.41)	**66.92**	(26.50)	17.26	(12.45)	**25.95**	(10.41)	23.37	(18.28)
t	16.92	(10.27)	-9.61	(9.43)	13.81	(7.92)	6.85	(3.41)	3.41	(5.46)
Constant	603.40	(120.10)	514.64	(33.40)	546.94	(45.50)	485.17	(19.19)	427.99	(31.32)

3.1 Preliminary Evidence on Weight, Wages, and Employment Behavior

Preliminary examination of the data yields evidence of differences in optimal employment behavior and wages related to body mass. While this study treats body mass as a continuous variable both theoretically and empirically, the following statistical analyses use an indicator function for whether the individual is obese.[3] Table 3.4 contains the results of fixed effects regressions of wages on a dummy variable for whether the individual is obese, years of experience in each of the five occupational categories, indicators for if the individual has graduated high school and college, family state, and a time trend. The results indicate that obese individuals incur wage penalties for their mass, but these penalties are statistically significant only in 'white-collar' occupations. Additionally, returns to own and cross-occupational experience vary by occupation. Experience in the five categories are not rewarded equally.

The data also show that individuals of different body mass likely have differences in experience from the five occupational categories. Figure 3.1 shows that obese individuals work in white collar occupations in lesser proportions than the non-obese. This pattern is particularly strong when individuals are young. Since these are the same occupations which exhibit wage penalties for obesity in the regressions above, wage differences may to some extent induce the

[3]The Centers for Disease Control define obesity as a Body Mass Index (kg/m^2) of 30+.

differences in observed employment behavior. Another implication of the regressions and graphs is that experience accrued in a given period may partially be determined by weight in earlier periods. Because experience affects future wages, understanding the relationship between body mass and wages requires understanding how body mass influences optimal employment behavior. Note from the regression and bar chart that obese appear to sort into the occupations in which experience garners lower returns. Experience in the blue collar and service jobs is minimally valued in the white collar occupations. The obese and non-obese also differ in their occupational transition patterns. Tables 6.6 and 6.7 summarize these differences.

Figure 3.2 depicts the difference in average real wages between the obese and non-obese, for each of the five occupational categories, as individuals age over the sample period. While the obese earn less than the non-obese in all five categories, this difference in real wages for white collar occupations quadruples over the sample period. Obese workers earn approximately one dollar per hour less than their non-obese counterparts at age 25, but four dollars less at age 49.[4] This growth may be partially explained by the early-age differences in employment behavior, ever increasing weight of the obese, dynamic sorting behavior, or perhaps changes in the requirements of these jobs and what effect body mass has on an individual's ability to fulfill those requirements.

3.2 Dictionary of Occupational Titles and Occupational Information Network

The data used for the construction of indices of job requirements, discussed in Section IV, come from the DOT and O*NET. The DOT was created in 1938 by the U.S. Department of Labor to assist job seekers and was periodically updated to capture new jobs or changes in required skills in existing jobs. The data on job requirements are taken from the 1977 edition, 1982 updates, 1986 updates, and 1991 revision. The DOT contains very coarse categorical information on requirements of over 12,000 tasks, but was primarily focused on blue-collar and industrial jobs. The DOT categorized the physical requirements of occupations based upon strength: Sedentary, Light Activity, Moderate Activity, Heavy Activity, and Very Activity.

[4]Real wages are calculated using 1983 as the base year.

Figure 3.1: Occupational Sorting - Obese and Non-Obese Workers by Occ Category

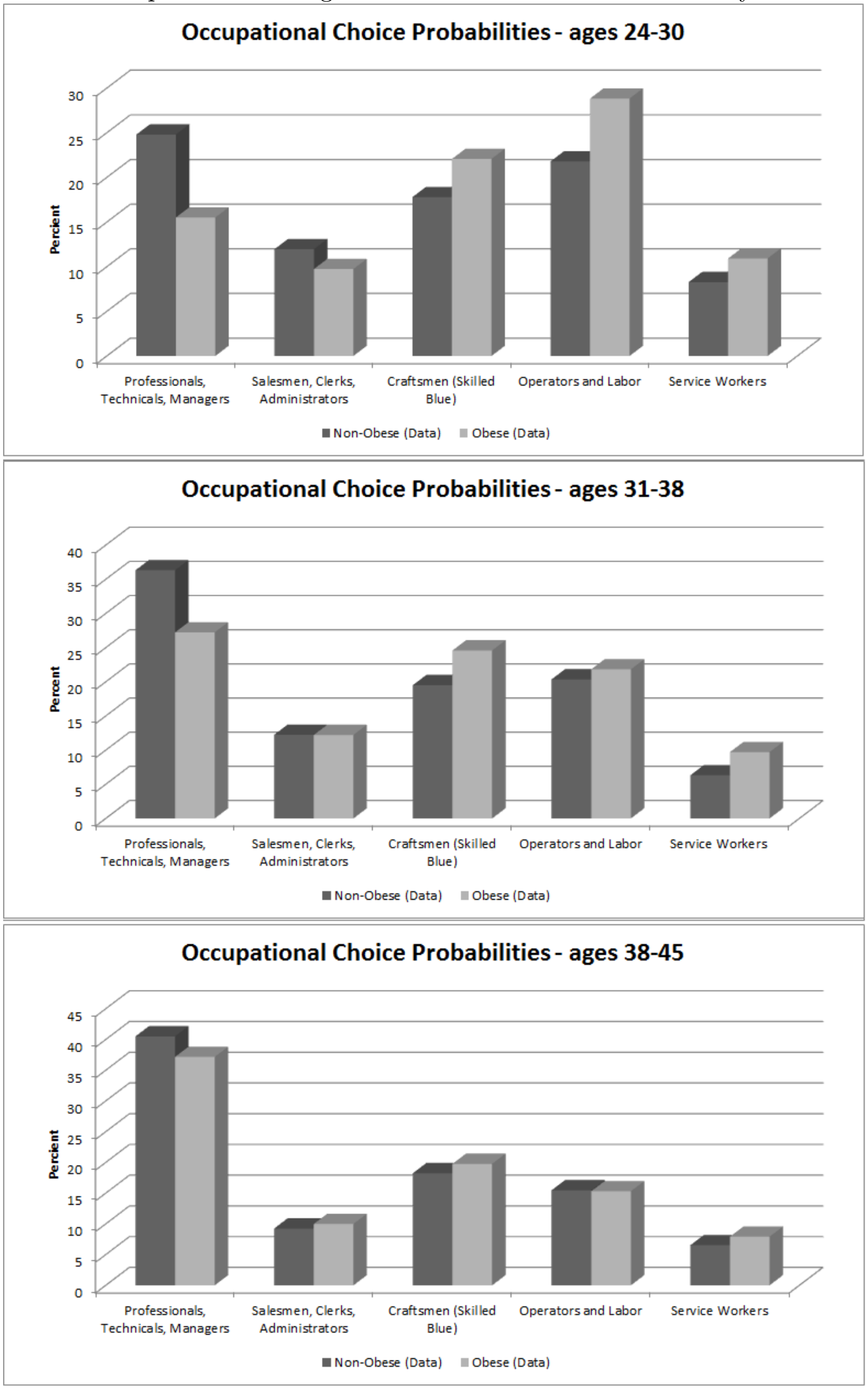

Figure 3.2: Mean Differences in Wages - Obese and Non-Obese Workers by Occ, by Age

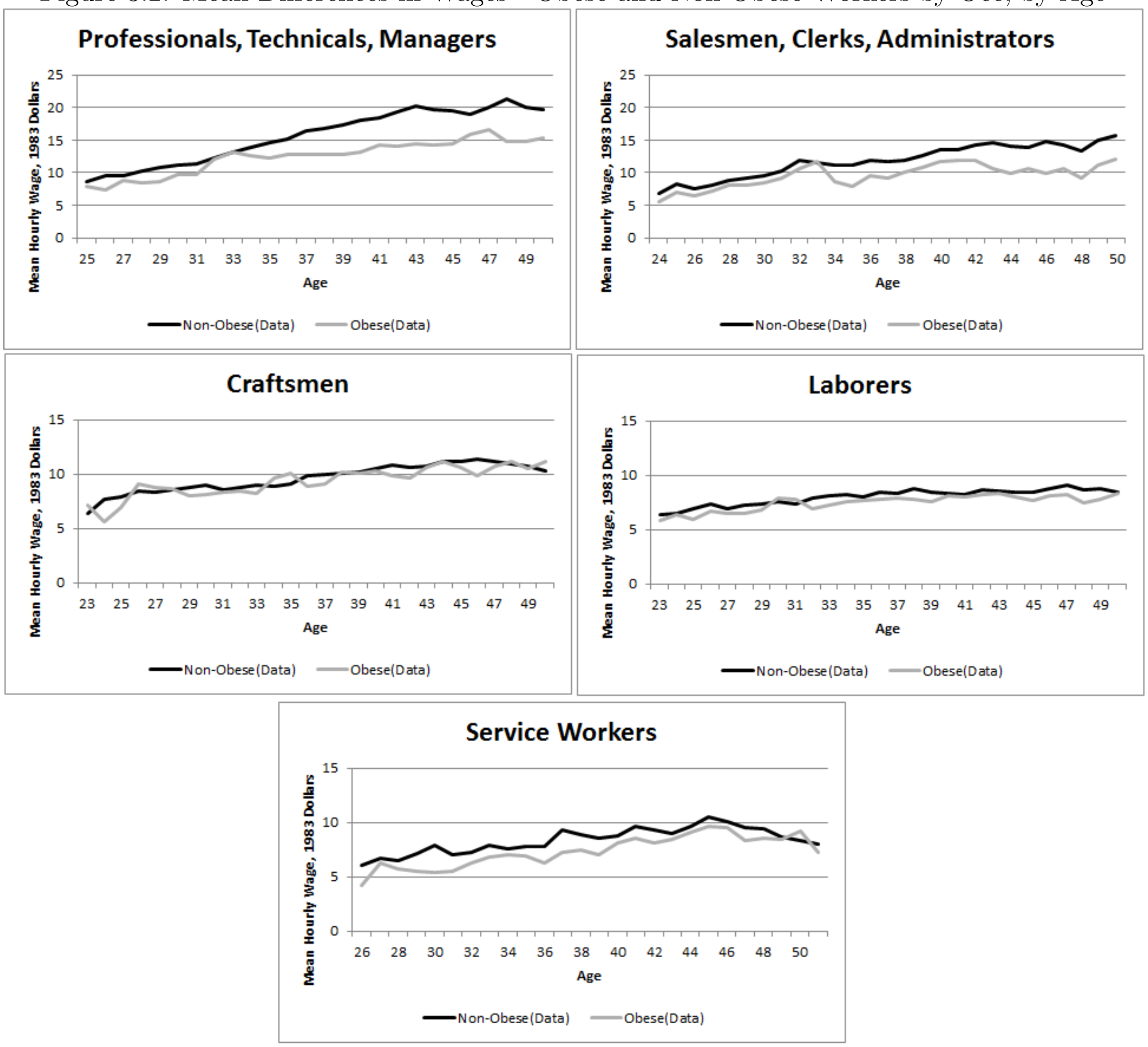

Table 3.5: Summary Statistics of DOT Requirements for occupation categories - 1977

Variable	Mean	Std. Dev.	Min.	Max.
Physical Requirements				
Prof/Tech/Mgr	0.694	0.366	0	3
Sales/Clerical	0.599	0.386	0	1.429
Craftsmen	1.779	0.53	0.857	3
Operatives/Labor	1.988	0.687	1	4
Service	1.501	0.446	0.833	3
Mathematical Requirements				
Prof/Tech/Mgr	3.825	0.747	1.75	6
Sales/Clerical	2.609	0.446	1.333	4
Craftsmen	2.489	0.655	1	4
Operatives/Labor	1.734	0.699	1	5
Service	2.163	0.59	1	5
Literary Requirements				
Prof/Tech/Mgr	4.445	0.639	2.333	6
Sales/Clerical	2.927	0.684	1.571	5
Craftsmen	2.621	0.627	1.231	4
Operatives/Labor	1.877	0.682	1	4
Service	2.676	0.825	1	5
Social Requirements				
Prof/Tech/Mgr	5.040	0.363	0	8
Sales/Clerical	2.401	0.418	0	6
Craftsmen	2.083	0.344	0	5
Operatives/Labor	1.527	0.261	0	4
Service	2.595	0.492	0	6

The verbal and mathematical demands of occupations were rated on a categorical scale from one to six. The 'people' aspect of an occupation was determined on a nine-point hierarchical scale. The summary statistics of the DOT ratings are in Table 3.5. More details are available in the appendix.

In the mid-1990s, the DOT was deemed obsolete and replaced with the O*NET, the first release of which was in 1998. In contrast to the DOT, the O*NET is aligned with the Census system of occupation classification and provides information on between 850-1000 'job families'. The O*NET focus is more on white-collar occupations and on information and service jobs, and it contains much finer numerical ratings (on level and importance) for far more requirements per occupation. Already on its fourteenth revision, the O*NET is updated far more consistently and comprehensively than the DOT. For the latter half of the sample, the data from the O*NET come from releases 1.0, 4.0, 5.0, 7.0, 9.0, 11.0, 12.0 and 13.1. The section on empirics details the process of converting the rich data in the O*NET to be comparable with the DOT.

3.3 ACCRA Data on Food Prices

To construct series on food price indices, I use data from ACCRA formerly the inter-city cost of living index. The group publishes quarterly prices on costs of commonly purchased items as reported by Chambers of Commerce in over 200 towns, cities, and Metropolitan Statistical Areas. The items priced in the data include many food items, such as T-bone steaks, ground hamburger, iceberg lettuce, tomatoes, canned green beans, 2-piece fried chicken meals, McDonalds quarter-pounders, and Pizza Hut/Pizza Inn 12-inch pizzas. I utilize 4th quarter data from 1976 to present for at least 200 cities or metropolitan statistical areas. I construct two food price ratios: fast-food-to-produce and processed-foods-to-produce. These are linked to the Geocoded NLSY primary data. These indices proxy for the costs of consuming healthy food relative to unhealthy food over the sample period. Utilizing ratios rather than levels will mitigate the confounding factors of both regional variation in cost of living and food prices and changes in food price levels over time. Summary statistics for the ACCRA indices are available in the data supplement in the appendix.

Chapter 4

Dyamic Stochastic Discrete Choice Model

I specify a dynamic stochastic model of employment behavior in which weight and the requirements of the job affect both the distribution of wages and non-monetary costs of each alternative. The empirical section then provides details of the solution and estimation. Subsection 1 defines the set of alternatives. Subsections 2 and 3 define the components of contemporaneous utility from each alternative. Subsections 4, 5, 6, and 7 detail the distributions of stochastic variables and define how current period decisions affect future utility. Subsection 8 assembles these components to formulate the individual's dynamic optimization problem in a value function framework.

4.1 Set of Alternatives

In this model agents jointly decide whether to work, how much to work, in which occupation to work, and whether to attend school. There are a total of 23 alternatives, $hj \in HJ$, available to an individual in each discrete period. The employment alternatives, h, are:

$$\begin{array}{lcl} h=1 & : & \text{work part time: weekly hours} \in \{15,34\} \\ h=2 & : & \text{work full time: weekly hours} \in \{35,49\} \\ h=3 & : & \text{work more-than-full-time: weekly hours} \geq 50 \\ h=4 & : & \text{work part-time and attend school part-time} \\ h=5 & : & \text{not work and attend school full time} \\ h=6 & : & \text{not work and attend school part time} \\ h=7 & : & \text{neither work nor attend school} \end{array} \tag{4.1}$$

The occupational alternatives available to an agent each period are denoted by j:

$$
\begin{array}{lll}
j=0 & : & \text{No occupation} \\
j=1 & : & \text{Professionals,Technicals, Managers} \\
j=2 & : & \text{Salesmen, Clerks, Administrative workers} \\
j=3 & : & \text{Craftsmen} \\
j=4 & : & \text{Operatives and Laborers} \\
j=5 & : & \text{Service workers}
\end{array}
\tag{4.2}
$$

If an agent chooses an employment alternative that includes work, ($h \in \{1, \ldots, 4\}$), he also chooses an occupation($j \in \{1, \ldots, 5\}$) jointly with that employment alternative. If an agent chooses an employment/school alternative which does not include working, ($h = \{5, 6, 7\}$), then $j = 0$ by definition. The combination of the four h alternatives that involve work times the 5 occupational categories plus $h = \{5, 6, 7\}$ comprises the set of 23 alternatives. These occupational classes are fairly descriptive coarse bins for the actual jobs people perform. Reducing the 1980 Census Occupation Codes into five skill-categories has two benefits: increasing feasibility of estimation in a discrete choice framework and reducing measurement error regarding occupational classification.[1] Aggregating all occupations into these five categories implies that experience is perfectly transferable within these categories.[2] [3] The discretized alternatives for hours worked (full-time, part-time, or overtime) corresponds to the

[1] Per Keane and Wolpin (1997) and verified by my own investigations, there is some measurement error in the NLSY occupation reports. During the survey, respondents tell interviewers what they do for their job, their tasks, responsibilities, et cetera. The interviewer then follows the Dept. of Labor Guidelines and assigns the Respondent a Standardized Occupation Code (SOC). There are many incidents in the data where an individual stays with the same firm, but oscillates between two SOC codes (usually between a specific job and a relevant miscellaneous category). At a sufficiently fine level of delineation between occupations, interviewer interpretation can be a source of measurement error. Simplifying the occupational alternatives to 5 classes virtually eliminates the artificial variation in occupational choice due to interviewer interpretation.

[2]While this assumption is an oversimplification, it is reasonable that experience within each category would be considered far more transferable than experience between categories. In the data set, agents with highly specialized occupational experience, (e.g. chemical engineers, surgeons, welders) seldom switch occupations once some human capital is accrued in that field. For these reasons, concerns about properties of transferability of experience are minimized.

[3]The cost of coarse aggregations of occupations is that of neglected intra-category heterogeneity between COC code occupations. The purpose of the model is to examine the differences in employment decisions between the obese and non-obese. If the obese and non-obese have great differences in intra-category sorting, that would necessitate greater refinement of the set of occupational alternatives. Examination of the data has revealed that to not be an issue. Evidence is available upon request.

U.S. Department of Labor's definitions for these terms. [4] The indicator d_t^{hj} equals one if employment alternative h and occupation j are chosen in period t, and zero otherwise, and $\mathbf{d}_t = \big(d_t^{hj}, (\forall j \in \{1, \ldots, 5\} | h \in \{1, 2, 3, 4\}), j = 0 | h \in \{5, 6, 7\}\big)$.

Agents make their first decisions at age 17, one year later than in the classic Keane and Wolpin framework(Keane and Wolpin, 1997).[5] In every period, an agent receives a job offer from each of the five occupation classes with probability one. Agents observe their wage offers and subsequently choose their occupations jointly with the number of hours to work. It is further assumed that the occupation-specific hourly wage offer is applicable for all alternatives involving that occupation, i.e. part time, full-time, over-time or work/school combination. The theoretical belief underlying this assumption is that wage offers are a function of the individual's education, previous experience, skill endowments, and other characteristics (observed or unobserved). This assumption also implies that any wage shocks (interpreted as demand shocks) that influence wage offers for a worker with given characteristics in a given occupation would affect wage offers identically across all hours-categories within that occupation. It is true that in many cases, not all hours/options may be available to all agents. However, agents are observed working part-time, full-time, and overtime in each occupation; and pursuing jobs that require (or permit) working more or less than full-time hours is a choice. Since the data do not contain information about any unaccepted job offers, modeling the employment alternatives as fully as possible took precedence over the computationally infeasible task of accounting for all labor demand frictions. Schooling decisions are modeled for two reasons. First, educational attainment is a critical factor in determining employment behavior over the life cycle. Second,

[4] Because the number of alternatives increases the complexity of solution, the model does not permit all possible combinations of part-time/full-time work and part-time/full-time school. Full-time school and working are not considered options. When an individual is enrolled in school full time, the schooling supersedes his work. While rare, the decisions of individuals who work full time while attending school part time are handled with a slight compromise. In a total of 108,031 observations (discussed further in the data section), fewer than 400 agents chose to work a full time occupation and attend school part time. In the less than 1,000 of these incidents, the hours worked was recoded to the top end of the part-time range, 34 hours. Thus, income distortions are minimized without incurring the cost of an additional five alternatives which have very small probabilities of being chosen. The total observed frequency with which the 23 alternatives are chosen is available in appendix A.

[5] NLSY 1979 cohort does not record agents weight until 1981. Modeling agents' decisions at age 16 would require additional computational issues for initial conditions based on unobservable weights in periods before 1981.

there is a significant negative relationship between educational attainment and weight. Education entering a period t is captured by accumulated years of school. Because the number of alternatives increases the complexity of solution, the model does not permit all possible combinations of part-time/full-time work and part-time/full-time school. Agents can either go to school full time, part time, or attend school part time in conjunction with working part time. I assume that any work experience gained while attending high school does not impact post high school decisions. The model does not therefore differentiate between attending high school while working and attending high school and not working.[6] I allow for degree attainment based on years of schooling only, rather than add of a degree completion decision to the model.[7]

The information state vector $\mathbf{S_t}$ contains the following variables: age, marriage/spousal earnings, number of kids, years of schooling, Body mass, years of experience in each of the five occupational categories, and the occupational alternative chosen in the previous period. Known to the agent, but not the econometrician unobserved heterogeneity, which includes a time-invariant component ϕ and alternative-specific, time-varying, idiosyncratic component ϵ_t^{hj}, to be discussed in more detail below. At the beginning of period t, the individual then observes his wage offers. The period t alternative defines the evolution of the state variables at the end of the period (defined here as a year). The individual's state variables entering the subsequent period reflect the accrued work experience or accumulated schooling. Body mass, marital status, and number of kids updated based on stochastic realizations and the period t

[6]If an agent is observed to advance a grade during high school range, they are classified as attending full time school. If an agent is observed going to college and working full time, they are recoded as working part time (albeit at the top of the hours range) and attending school part time. The combination of full time work and full time school is observed 685 times (total of 323 people) of a sample of 4699 individuals (approx 108,000 total observations).

[7]There has been much debate in the labor economics literature about whether degree attainment supersedes years of schooling in terms of impact on wages. In this version of the model, I treat having twelve completed grades as having a high school diploma and 16 completed grades as having a bachelor's degree. In 1988, the first year that "highest degree attained" was properly reported, 89.3% of the 912 individuals with 16 years of schooling had earned their bachelor's degree. Including those with 17+ "grades completed" only increased the proportion to 90.4%. Since less than 1.5% of the total sample went to school for 16 years and did not earn a bachelor's degree, I treat the two conditions as equivalent. High school graduation rates conditioned on years of schooling are comparable. Of those who have completed twelve grades exactly, over 93% have graduated high school. While advanced degrees are present for a non-trivial portion of the sample (approximately 10%), advanced degreed individuals do not have drastically different occupational sorting profiles nor wage profiles than those whose highest degree is a Bachelor's.

decision.

4.2 Per-period Utility and Constraints

The contemporaneous utility of an alternative, hj, is a function of consumption, leisure, the annual fixed costs of participating in an occupation, variable costs by hours worked, and any transitional costs of changing occupational categories between periods. In the function below, c_t represents consumption, $h_t(\mathbf{d}_t)$ defines the number of hours worked and/or spent in school for the set of alternatives, and $M_j(\cdot)$ and $M_s(\cdot)$ are the fixed costs of occupation j and schooling alternative s, respectively. The interpretation of these fixed costs is discussed in section 4.3. $N(h_t(\cdot))$ is the utility of working h_t hours (also detailed in 4.3).

Information available to an individual at the start of period t, $\mathbf{S_t}$, influences the utility of each alternative. Per-period utility for each alternative, conditional on both observed and unobserved information, is:

$$\begin{aligned} u(\mathbf{d}_t, \mathbf{S_t}, \epsilon_t|\phi) &= \frac{c_t^{1-\alpha} - 1}{1-\alpha} \\ &- \left(\sum_j \big[M_j(\mathbf{S}_t|\phi) \big(\sum_{h=1}^{4} d_t^{hj} \big) \big] + M_s(\mathbf{S}_t|\phi) \big(\sum_{h=4}^{6} d_t^{hj} \big) + N(h_t(\mathbf{d}_t), \mathbf{S}_t|\phi) \right) + \epsilon_t^{hj} \end{aligned} \tag{4.3}$$

Consumption is constrained by income (which includes a coarse discretization of spousal income) as savings and financial markets do not enter the model. Time is constrained by the time endowment per week Ω and is allocated between labor supply, h_t, and leisure, l_t. Time spent on education counts as "non-leisure" time in the model. An agent is assumed to spend 20 hours per week on school if attending part time and 40 hours per week if attending full time. If an agent pursues a part-time work, part-time school combination, his total non-leisure time is the sum of his hours spent working plus the 20 hours per week for part-time schooling. Because home production time is not identified in the data, I only separate time into hours working and hours not working. The preference shocks in the utility function, ϵ_t^{hj} are assumed to be i.i.d.

Type 1 Extreme Value. The budget and time constraints are specified as:

$$\begin{aligned} c_t &\leq w_t(\mathbf{d}_t, \mathbf{S}_t)h_t(\mathbf{d}_t) + I(\mathbf{S}_t) \\ \Omega &= l_t + h_t(\mathbf{d}_t) \end{aligned} \tag{4.4}$$

where w_t and h_t are hourly wages and hours that depend on the observed state vector and the alternative chosen in period t. Similarly, the fixed and variable costs of employment or hours in different occupations vary by observable (and unobservable) characteristics. The I_t denotes unearned income (i.e., spousal income if married), and Ω represents the individual's total amount of time in a given period.

4.3 Non-Monetary Costs of Alternatives: Fixed, Switching, and Variable

The model assumes that individuals receive wage offers from every occupational sector in each period. However, individuals in the data do not always select into occupations with the frequency one would expect if individuals solely maximized wealth and there were no labor demand frictions. Realistically, the demand side of the labor market may impose constraints on employment in particular occupations for some people depending on their state. On the supply side, there may be non-pecuniary aspects of a particular occupation that are valuable to an agent every period that he works in that occupation (i.e., preferences). Because a goal of this research is to discern why there are weight-related differences in occupational sorting, the model includes three types of costs for pursuing employment alternatives. First, the model includes per-period fixed costs of participating in each occupation that depend on one's human capital and body mass. While these fixed costs may be the result of demand side frictions and/or employer preferences, they are not specifically attributable to either. Second, the model includes marginal costs of working additional hours. By allowing individuals to choose how much they work upon receiving a wage offer, the model captures if the marginal costs of working more varies by weight and job requirement. Because the decision to work more or fewer hours is made conditional on receiving an offer, these costs are attributable to worker utility. Third, the model includes costs of transitioning into occupation j from another occupation, j'. These switching costs are allowed to vary by body mass. Unlike the per-period fixed-costs, which may be due to demand or worker concerns, the switching costs are attributed to labor-demand frictions such as search costs and employer preferences.

The state variables that affect the fixed costs are age and education, where the vector $\mathbf{E}_t$ contains three elements: an indicator for having accrued at least 12 years of school up to period t, an indicator for having accrued at least 16 years of school up to period t, and completed years of schooling up to period t. The fixed costs of occupational participation also depend on the period t job requirements $\mathbf{J}_{jt} = [J^p_{jt}, J^m_{jt}, J^s_{jt}]$, which include the physical, mental, and social requirements of occupation j at time t and ϕ^k_j, an occupation specific match parameter.[8] Body mass, B_t, captures an individual's distance from a "healthy weight".[9] The per-period fixed cost of participating in an occupation j, inclusive of any switching costs, is expressed as:

$$\begin{aligned} M_j(\mathbf{S_t}|\phi) = {} & \alpha^j_0 + \alpha^j_1 a_t + \alpha^j_2 \mathbf{E}_t + \alpha_3 \mathbf{J}_{jt} + \alpha^j_4 B_t + \alpha_5 \mathbf{J}_{jt} B_t \\ & + \sum_{j' \neq j} \alpha^j_{5+j'} \mathbf{1}(d^{hj'}_{t-1} = 1) + \alpha^j_{11} \sum_{j' \neq j} d^{hj'}_{t-1} B_t + \alpha^j_{12} \sum_{j' \neq j} d^{hj'}_{t-1} a_t + \rho^J_j \phi \end{aligned} \tag{4.5}$$

Because the levels of job requirements vary across occupations, the coefficients on the variables for job requirements are fixed across occupations. These "fixed costs" by definition should be thought of in wage equivalents. Body mass interacts with occupation as well as job characteristics. While including the switching costs will separate some of the labor demand frictions, the fact that employer preferences cannot be perfectly separated from flow utility should be kept in mind when interpreting these parameters. However, as in the wage equations described below, including the occupation-specific job requirements and the interactions with weight status permits a deeper examination of the systematic differences in occupational choice frequencies between the obese and non-obese. That is, they inform whether job requirements make it more costly for higher weight individuals to work in a particular occupational category. The non-pecuniary costs of schooling depend on age (a_t), level of schooling, whether the individual was

[8] Job requirement indices are discussed in greater detail in the data section.

[9] The Centers for Disease Control define "healthy weight" to be a body mass index that ranges from 18-25. There are only six individuals in my sample who fall into the "below healthy range" category at any point during the sample period.

out of school in the preceding period, and the interaction of age and returning to school.

$$M_s(\mathbf{S_t}|\phi) = \alpha_0^s \mathbf{E}_t + \alpha_1^s \big(\sum_{h=4}^{6} (d_{t-1}^{hj} \neq 1) \big) + \alpha_2^s a_t + \alpha_3^s a_t^2 + \alpha_4^s a_t \big(\sum_{h=4}^{6} (d_{t-1}^{hj} \neq 1) \big) + \rho^S \phi \tag{4.6}$$

The individual also incurs variable costs of working more than the minimum threshold of 20 hours (i.e., part-time). The expression for the variable costs of labor supply, $N(h_t(\mathbf{d}_t))$ contains many of the same arguments as the occupational non-pecuniary-benefits expression, adding interactions with h_t. In the model, hours pursuing education and work are treated the same, up to the differences in job requirements, as discussed in the data section. Because the model assumes that the labor demand frictions are captured by the occupation-specific fixed costs of participation and the switching costs, these variable costs of working hours beyond the minimum can thus be interpreted solely as representing worker preferences for working more (or fewer) hours performing occupations with specific requirements. I can therefore assess how utility from working a particular number of hours at a job with particular requirements varies by weight.[10][11]

In this expression, m_t is a variable for whether the individual is married, a_t is the individual's age at time t, and k_t is the number of children the individual has at time t. The variable costs

[10] It is also possible that labor demand frictions restrict the hours alternatives available to agents. There is some evidence in the literature (and in the data) to alleviate that concern. Altonji and Paxson (1988) examine the labor supply preferences of hours constrained workers and hours/wage trade-offs. They find that approximately 27% of workers surveyed in the PSID in 1982-1983 report they wish they could work more hours. However, among those who switched jobs in the ensuing period, only 6% remained feeling "under-employed" after the switch. The average difference in hours worked for those who went from feeling "under-employed" to fully employed was 4.4 hours. These results indicate that while labor demand frictions may interfere with workers getting their exact preference of hours, those workers are a minority, and those hour restrictions are small in magnitude relative to the discrete hours worked alternatives in this model. Further, if workers truly sought 55-60 hours per week, but could only get 40 at their primary job, they could pick up a second job. While the model does not account for second jobs, only approximately 4-5% of the sample works a valid second job currently with their first job in most sample years.

[11] These variable costs of working additional hours may also capture weight-related differences in utility from leisure time. However, as the model only permits individuals to allocate their time endowment between working and non-working time, I cannot separately identify the effects of body weight on utility from leisure.

of hours worked are:

$$N(h_t(\mathbf{d}_t), \mathbf{S_t}|\phi) = h_t(\mathbf{d_t}) \cdot \Big(\psi_1 + \psi_2 m_t + \psi_3 k_t + \psi_4 B_t + \psi_5 h_t(\mathbf{d_t}) B_t + \psi_6 \mathbf{J}_{jt} + \psi_7 \mathbf{J}_{jt} B_t + \psi_8 [a_t] + \psi_9 [a_t^2] + \rho^N \phi\Big) \tag{4.7}$$

Although hours worked, $h_t(\mathbf{d_t})$ is reported as an integer, the set of alternatives related to labor supply is polychotomous. If a specific value of hours is needed for calculation of the value function, I use 25 hours for part-time work, 40 hours for full-time work, and 50 hours for over-time work. For alternatives that are observed in the data, I use the observed value of hours worked to calculate $N(h_t(\mathbf{d}_t), \mathbf{S_t})$.[12] [13]

4.4 Distribution of Wages

The model assumes agents are forward looking. When an agent makes his employment decision, he does so taking into consideration how his decision this period affects his expectations of future wage offers. These expectations over future outcomes then affect the agent's decision today. When estimating the model, calculating the probability that an agent chooses an alternative requires taking expectations over the wage distributions of unobserved wage offers. The distribution of wages, not just the conditional mean, is meaningful in solution to the model and estimation of parameters. To model the distribution of wages, it is often assumed that wages follow a continuous distribution (e.g., Keane and Wolpin, 1997; Sullivan, 2010). Rather than impose a parametric distribution on an error term and estimate a conditional mean, I estimate the density of wages using Conditional Density Estimation (CDE). The density of wages is:

$$w_{jt} \rightsquigarrow f_W(j, \mathbf{S}_t, \mathbf{J}_{jt}, \phi) \tag{4.8}$$

[12] Some transformation of h_t may be needed for proper identification of the parameters in $N(\cdot)$ from the parameters in $M_j(\cdot)$. This is further discussed in the identification section.

[13] Most studies that examine occupational choice or labor supply decisions of males do not include marital state nor number of children. While this initial version of the model is restricted to white males, I plan to extend the model to include women. When including women in the sample, capturing the dynamic interaction between family, employment behavior, and weight will be extremely important.

where wage is determined by the state vector ($\mathbf{S_t}$), which includes work experience, education, and body weight; and job characteristics. Unobserved occupation-specific "skill endowment", ϕ, also influences wages. The coefficients on the interaction between body mass and the vector of job requirements determine how much of the observed wage differences between individuals of different weights can be attributed to contemporaneous expected differences in productivity. The coefficients on the occupational dummies interacted with body mass provides the upper bound for the wage differences in each occupation attributable to employer preferences.

4.5 Evolution of Human Capital State Variables

The goal of the model is to capture the dynamics of weight, wages, and employment behavior over the life course. Human capital - or years of work experience and years of schooling, as well as one' employment/schooling state in the previous period - has dynamic implications for wages and current period utility. This model allows work experience to accrue faster for agents who choose to work more hours. If an individual that works longer hours (and accrues more human capital) in a given occupation tends to gain weight faster than his less career-motivated peers, a failure to keep track of differences in accrued human capital will lead to bias in the estimation of weight-based wage penalties. Conversely, if being heavier means that it requires more energy to work (i.e., creates greater disutility), then allowing accrual of experience to differ for part/full/over-time alternatives is necessary to accurately capture the effects of weight on employment behavior over the individual's adult lifetime. Second, there is the complication of overtime exempt versus non-exempt employees. Particularly in salaried jobs, many relatively high paying jobs come with expectations of working more than forty hours. When an individual chooses a job, he chooses a job where income is earned and time is sacrificed, fully aware of the expectations. However, for individuals with salaried jobs, there is no contemporaneous benefit to working longer hours even when a wages/hours combination with longer hours is chosen.[14] Yet in each period, 15% of the individuals in the sample are seen to work more than 50 hours per

[14]This is true by construct in the model since I am not modeling layoff probabilities. I could add a term in the wage equation for hours worked in the preceding period which would capture negative wage shocks as a result of working less in a given period.

week. The majority of these events are observed in jobs which, in reality, are often salaried.[15] Therefore, for rational, utility maximizing agents to put forth effort beyond the stereotypical "nine to five" , they must be compensated in the future. This feature is incorporated into the model by having higher levels of labor supply accelerate the accrual of human capital, x_t^j. The state variable x_t^j denotes "full-time-years of experience" in occupation j entering time t. The evolution of work experience in each occupation is:

$$x_{t+1}^j = \begin{cases} x_t^j & \text{if } (\sum_{h=1}^4 d_t^{hj}) = 0 \qquad \text{(no employment in occupation } j\text{)} \\ x_t^j + \frac{1}{2} & \text{if } d_t^{1j} = 1 \text{ or } d_t^{4j} = 1 \qquad \text{(part-time employment in occupation } j\text{)} \\ x_t^j + 1 & \text{if } d_t^{2j} = 1 \qquad \text{(full-time employment in occupation } j\text{)} \\ x_t^j + \frac{3}{2} & \text{if } d_t^{3j} = 1 \qquad \text{(over-time employment in occupation } j\text{)} \end{cases} \tag{4.9}$$

Likewise, the model accounts for accumulated years of schooling entering period t, ed_t, and is independent of occupation, but not work behavior in the previous period. Years of schooling accrue as follows: [16] :

$$ed_{t+1} = \begin{cases} ed_t & \text{if } d_t^{hj} = 1, h = 1,2,3,7 \qquad \text{(no schooling)} \\ ed_t + \frac{1}{2} & \text{if } d_t^{hj} = 1, h = 4,6 \qquad \text{(part-time-schooling)} \\ ed_t + 1 & \text{if } d_t^{hj} = 1, h = 5 \qquad \text{(full-time schooling)} \end{cases} \tag{4.10}$$

---

[15] The distinction between exempt and non-exempt occupations is not modeled in this dissertation

[16] The accrual of education as an endogenous state variable brings the discussion back to the alternatives where school *and* part time work are chosen. The pragmatic justification for forcing work and school to be part time is that in reality, school and work are distractions from one another. Going to school at night provides some distraction from work. Thus, though individuals may work the hours, they do not reap the benefit from a "full year" increase in their experience. Those who work and go to school in a given year accrue a half year's advancement in both work and their in-school occupation. While this results in some slight discrepancies between the model and individual reports of the highest grade completed, the key constructed cutoff points, high school degree and bachelor's degree, track extremely well with the observed degree reports.Approximately 1% of the observations in the data have degree mismatches (i.e., an agent is modeled to have a degree when he does not in the data or vice versa)

4.6 Additional State transitions - Marriage and Children

There are four possible values for marriage (M_t), delineated by spousal earnings.[17] An agent is single, married to a non/low earner, married to an average earner, or married to a high earner. This earnings distinction is necessary for two reasons. First, differences in spousal earnings are likely to create different incentives for labor force participation and labor supply. Ceteris paribus, the spouses of high earners should respond differently to wage shocks than spouses of low earners. I allow an individual's weight to stochastically influence his marriage and spousal income, as in Tosini (2008). As spousal earnings in turn subsequently affect the relative utility appeal of employment alternatives, these differences are worth capturing. The marriage state transitions stochastically, but exogenously. The marriage transition probabilities (in log odds) are specified as follows:

$$ln\frac{P[M_{t+1}=m'|M_t=m,\mathbf{S_t},\mathbf{d_t}]}{P[M_{t+1}=0|M_t=m,\mathbf{S_t},\mathbf{d_t}]}=\delta^M_{m'}\otimes[1,M_t,Ed_t,B_t,B_t*M_t,a_t,Y_t],m'=1,2,3 \quad (4.11)$$

Similarly, the probability transition for number of children,K_t, is specified (in log odds) as:

$$ln\frac{P[K_{t+1}=K_t+1|\mathbf{S_t},\mathbf{d_t}]}{P[K_{t+1}=K_t|\mathbf{S_t},\mathbf{d_t}]}=\delta^K\otimes[1,a_t,K_t,Ed_t,[M_t>0],h_t] \quad (4.12)$$

I assume that six or more children occurs with probability zero. Marriage status and children themselves do not provide utility. Marriage is included as a stochastic state to capture variation in employment decisions resulting from variation in unearned spousal income, which enters the budget constraint. Due to the concavity of the utility function in consumption, holding marginal utility of leisure constant, an increase in unearned spousal income would decrease the optimal number of hours worked. Children influence stochastic weight gain (explained below).

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[17] While I initially estimate the model using white males in the data set, I want to include women in future versions. Previous research has indicated that weight-related wage penalties and weight-related occupational sorting behavior of women display marked differences from those of men. So, while including the family states for the men may or may not be important, including the contemporaneous family state and expectations over future family states is crucial for modeling the forward-looking employment behavior of women. Since marriage only matters in this model insofar as it affects employment behavior and weight status, I do not model marriage and children as a decision, but rather as a stochastic, non-endogenous state variable using a conditional Markov process.

4.7 Weight Transition

Having modeled how weight can affect wages and decisions regarding occupation and hours worked, this section specifies how the model admits the possibility that employment decisions may affect weight. Employment behavior can affect weight both directly and indirectly. Direct effects come through on-job activity levels and number of hours worked at those levels. Food consumption and exercise behavior held constant, lower on-job activity levels equate to lower caloric expenditure. Principally due to limitations of the data, this model does not include an agent's control over food and exercise.[18] Despite not being able to observe these inputs into the weight equation, by including the endogenous determinants of the inputs, it is still possible to conduct inference on the indirect effects of employment decisions on weight. This issue is further discussed in the section on emipirics. In the model, body mass is conditioned on body mass in the preceding period, food prices, food supply factors, environmental factors, wages, and family states, the requirements of the occupation selected in that period, and hours worked. The state transition probabilities for body mass are estimated (and future expectations subsequently taken) using CDE. As with wages, estimation of the conditional density of body mass without imposing assumptions on the shape of the distribution is advantageous in examining how covariates of interest affect body mass over the support of the distribution. Conditional on body mass B_t in period t, the density of body mass in period $t+1$ is:

$$B_{t+1} \rightsquigarrow f_B(\mathbf{d}_t, \mathbf{S}_t, \mathbf{J}_{jt}, p^F, X_t^G, \phi) \tag{4.13}$$

where the X_t^G variables capture regional and time series variation in food prices, access to facilities, crime rates, number of fast-food restaurants per capita, etc.

[18] Recent work suggests that the omitted variable of endogenous exercise is not that problematic. Coleman and Dave (2011) use ATUS data and find that only 4% of total daily calorie expenditure is due to discretionary exercise, thereby reemphasizing the importance of on-job activity. However, the lack of insight into individuals' food choices remains an issue, albeit one which is addressable in part.

4.8 Optimization Problem

The objective of the individual is to choose alternatives at time t to maximize expected lifetime utility at time t conditional on his current state:

$$maxE\Big[\sum_{k=0}^{T-t} B^k U(\mathbf{d_{t+k}}, \mathbf{S_{t+j}}, \phi, \epsilon_{t+k}|\mathbf{d}_t, \mathbf{S_t})\Big]\forall t \in T \tag{4.14}$$

Lifetime utility at time t is represented by a value function using the Bellman formulation. In a finite horizon maximization problem where individuals' entire lives are observed, the value function in the terminal period is equal to the contemporaneous utility. However, individuals in this model continue to live beyond the periods where they are observed. Some appoximation is therefore needed to 'close' the model with a continuation payoff to capture future expected utility beyond the sample period. This is discussed in the next chapter.

The value function is comprised of current period utility and discounted expected future utility. The total current period utility can be separated into the deterministic utility from equation 4.3 and an alternative-specific i.i.d. preference shock:

$$\overline{U}_{hj}(d_t^{hj} = 1, \mathbf{S}_t, \phi) = U_{hj}(d_t^{hj} = 1, \mathbf{S}_t, \phi, \epsilon_t) - \epsilon_t^{hj} \tag{4.15}$$

In the empirical implementation, ϵ_t^{hj} is an additive econometric error (Rust, 1987). In the theoretical model, ϵ_t^{hj} is interpreted as an unobserved state variable (Aguirregabiria and Mira, 2010). The Bellman formulation of the alternative specific lifetime value function in state $\mathbf{S}_t$, conditional on unobserved heterogeneity ϕ, is:

$$\begin{aligned} V_{hj}(\mathbf{S}_t, \epsilon_t^{hj}|\phi) = \overline{U}_{hj}(\mathbf{S}_t, \phi) + \epsilon_t^{hj} + \beta \int_B f(\mathbf{d}_t, \mathbf{S}_t, \phi) \\ \sum_{k=0}^{1}\sum_{m=0}^{3} P[M_{t+1} = m|\mathbf{S_t}, \mathbf{d_t}]P[K_{t+1} = k|\mathbf{S_t}, \mathbf{d_t}]E[V(\mathbf{S}_{t+1}|\phi))|d_t^{hj} = 1]dB \end{aligned} \tag{4.16}$$

where $V(\mathbf{S}_{t+1}|\phi)$ is the maximal expected lifetime utility of being in state $\mathbf{S}_{t+1}$. The value function is conditional on the unobserved heterogeneity component ϕ. The expectation operator is taken over the future wage and preference shocks. I use quadrature with the estimated conditional density of wages to evaluate the expectation within solution to the model.[19] Let $\overline{V}_{hj}(\cdot) = V_{hj}(\cdot) - \epsilon_t^{hj}$. If we assume that ϵ_t^{hj} follows a Type 1 Extreme Value distribution, then maximal expected lifetime utility has the following closed form expression:

$$V(\mathbf{S}_{t+1}|\phi) = \lambda + ln(\sum_{hj} exp(\overline{V}_{hj}(\mathbf{S}_{t+1}|\phi)), \quad \forall t \tag{4.17}$$

where λ is Euler's constant. Furthermore, because the error term ϵ_t^{hj} is additively separable, the conditional choice probabilities take the following form:

$$p(d_t^{hj} = 1|\mathbf{S}_t, \phi) = \frac{exp(\overline{V}_{hj}(\mathbf{S}_t|\phi)}{\sum_{hj'} exp(\overline{V}_{hj'}(\mathbf{S}_t|\phi)} \tag{4.18}$$

The likelihood function consists of these choice probabilities, augmented to take expectations over unobserved wages as in Stinebrickner (2001) and Sullivan (2010), and transition probabilities for marriage, body mass, and number of children.

[19]This is discussed further in the next section.

Chapter 5

Empirical Implementation

Several features of the model are emphasized in the following discussion of the estimation of the theoretical model. Having discussed these features in light of empirical implementation, I conclude this section with a discussion of identification and construction of the likelihood function.

5.1 Conditional Density Estimation

Rather than assume normality of the (log) wage distribution and body mass distribution, I impose no distributional form and estimate the conditional density of (level) wages and body mass flexibly. Estimating the conditional density utilizes sequences of conditional probability functions to construct a discrete approximation to the density function of the outcome of interest, conditional on the explanatory variables listed above. As in Gilleskie and Mroz (2004), these conditional probability functions used in the sequences are logit probabilities. This technique has several beneficial features relative to the traditional approach of assuming a distribution and parameterizing moments (e.g. the mean and variance for a normality assumption) of the imposed distribution. First, CDE allows explanatory variables to have a different effect at different points of support of the distribution of wages. Recent work using nonparametric methods (Kline and Tobias, 2008) and quantile methods (Johar and Katayama, 2012) has shown that the effects of weight on wages varies over the distribution of wages. This same feature permits an assessment of whether the distribution of wages in a particular occupation magnifies or suppresses weight-related wage differences. Do occupations with high concentrations of low wages not ostensibly exhibit wage penalties for obesity because of lower skill requirements, or because wage penalties for obesity are far more pronounced at the top end of the wage distribution? CDE has the additional benefit of not imposing multiplicative separability of the variables in interpreting the levels of the logged variables. Gilleskie and Mroz (2004) show that expected wages (i.e., the first moment) can be approximated using the estimated density:

$$E[w_t|\mathbf{S_t}, \mathbf{J}_{jt}, \phi] = \sum_{k=1}^{K} \overline{w}(k|K) \cdot P[w_{k-1} \leq w_t < w_k|\mathbf{S}_t, \mathbf{J}_{jt}, \phi] \tag{5.1}$$

where $P[w_{k-1} \leq w_t < w_k|\mathbf{S}_t, \mathbf{J}_{jt}, \phi] = \lambda^W(k, \mathbf{S}_t, \mathbf{J}_{jt}, \phi) \prod_{j=1}^{k-1}[1 - \lambda^W(j, \mathbf{S}_t, \mathbf{J}_{jt}, \phi)]$, $\lambda^W(\cdot)$ is the logit probability that the individual's wage, conditional on his state, is observed in a given partition; and $\overline{w}(k|K)$ is the arithmetic mean of the wages observed in partition k. In solution to the model,expectations can be taken using this discrete estimated approximation rather than integrating over a continuously distributed error term. Similarly, the expectations and transition probabilities for body mass are:[1]

$$E[B_{t+1}|\mathbf{S_t}, \mathbf{d}_t, \phi] = \sum_{l=1}^{L} \overline{B}(l|L) \cdot P[B_{l-1} \leq B_{t+1} < B_l|\mathbf{S}_t, \mathbf{d}_t, p_t^F, X_t^G, \phi] \tag{5.2}$$

where $P[B_{l-1} \leq B_{t+1} < B_l|\mathbf{S}_t, \mathbf{d}_t, p_t^F, X_t^G, \phi] = \lambda^B(l, \mathbf{S}_t, \mathbf{d}_t, p_t^F, X_t^G, \phi)\cdot$
$\prod_{j=1}^{l-1}[1 - \lambda^B(j, \mathbf{S}_t, \mathbf{d}_t, p_t^F, X_t^G, \phi)]$, $\overline{B}(l|L)$ is the arithmetic mean of body masses observed in partition l, and $\lambda^B(\cdot)$ is the logit probability that the individual's body mass, conditional on his state, is observed in a given partition.

5.2 Indices of Job Requirements by Occupation

A primary contribution of this dissertation is the tracing of weight-based wage differentials and sorting differences to the physical, mental, and social requirements for the occupations. The raw data for requirements for jobs come from the Dictionary of Occupational Titles and its present day counterpart, O*NET, the Occupational Information Network. The DOT contains

[1] K and L are the number of quantiles into which the data for wages and weight are divided. Here, 25 was used for K and 20 was used for L.

information on over 12,000 jobs, many of which could be better characterized as tasks than positions for which an individual is solely hired. Aggregating these jobs up to five occupational classes is done in two steps. First using a crosswalk from ICPSR and my own work, I linked as many jobs as could be cleanly linked to a Census Occupation Code. An unweighted average of the requirements of these DOT formed the COC-level values for job requirements. Second, CPS weights were used to aggregate the SOC averages up to the Occupation-class-level values. Intrinsic variation in requirement values come from changes in the both from changes in reported values in DOT and O*NET revisions and from addition/subtraction of jobs between revisions. Extrinsic variation in requirement values comes from the variation in CPS weights change over time, changing the relative import of the SOC level values to the occupation class requirement values (e.g., computer systems analysts are much more heavily weighted in 2006 than 1980).

One obstacle in creating these indices was mapping the fine O*NET data into the coarser DOT. The DOT contained very coarsely scaled data on job requirements in less than 10 dimensions. The O*NET, by contrast, contains highly detailed information on what it takes to do a job, containing continuous scales of both level and importance (relative to the DOT's discrete 0-5) of over 50 elements. To overcome the difficulty in identifying changes in job requirements from 1991-1998 from changes to the DOT/O*NET rating system, I use a study by Felstead et al (2006) that uses survey data to examine how various skill requirements and prevalence of computers have changed in one-digit occupation classes from 1987 to 2006. If the authors report that physical requirements of an occupational category has changed less than 3%, I treat that as no real change. Using a regression with the subset of minimally changing jobs, I predict how O*NET values would translate to DOT values.[2] Conditional on this assumption, variation in predicted DOT ratings based on O*NET data can be interpreted as changes in job requirements. Graphs of the calculated job indices by occupation from 1977-2006 are available in the appendix.[3]

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[2]Regression results, and specific subsets of occupations used in this step will be made available shortly as a web appendix.

[3]In all five occupational categories, the social and mental requirements have increased over the sample period, which is consistent with the notion of skill-biased technical change (Autor et al., 2003). The hypothesis is that as computers have become more prevalent and more powerful, they have removed the burden of performing tasks

5.3 Permanent Unobserved Heterogeneity

The estimated model allows unobserved (as well as observed) heterogeneity of the individual to influence decisions and outcomes. This feature is important because correlation in unobservables across alternatives and outcomes (possibly due to genetics, persistent personality traits, etc.) could bias estimates of parameters if the correlation is not modeled. I allow permanent unobserved heterogeneity to enter the model through the ϕ terms and associated factor loadings (ρ). The factor loadings allow for a different effect of the unobserved ϕ in each expression. Approximating the joint distribution of this unobserved heterogeneity with a step function, estimating the factor loadings, mass points, and probability weights (π) removes the necessity of imposing distributional assumptions on the error term (Heckman and Singer, 1984). This discrete factor method has been shown to approximate well both normal and non-normal distributions (Mroz, 1999). Unobserved heterogeneity enters the fixed-costs of participation in each occupation and schooling, and the utility from working h_t hours. One factor loading is estimated for each alternative, with the factor loading on the outside option normalized to zero. The factor loading for scholing does not differ by employment status while in school. All unobserved hetergeneity is worker specific and permanently fixed. I abstract from all within-occupation firm-specific concerns such as worker-firm match values and heterogeneity among employers in their taste for employees of varying body weights.

5.4 Weight Inferences

The purpose of this dynamic model is not to explore why people gain weight. Rather the model correctly includes stochastic weight transitions that might be directly and indirectly influenced by schooling, employment, occupation, and hours decisions in order to capture the endogenous evolution of weight over the life cycle. This section discusses data limitations that must be

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which are "routine", thereby shifting the mental demands on workers to higher order thinking. Workers who 20 years ago spent their time sawing/cutting, now operate complicated machinery to accomplish the same tasks. Knowledge workers, who formerly spent time performing computationally intensive tasks, now spent more time on more strategic work. The physical demands of blue collar jobs have decreased over the last 30 years, whereas the physical demands of white collar work have risen slightly. These increases in demands are not drastic, but reflect a change from abject stationarity to some light motion. While on average workers have certainly migrated into more sedentary work over the sample period, not all occupations have become increasingly sedentary.

dealt with in order that weight may be modeled appropriately as a dynamic component of a relationship with possible two-way causality (given that there are differences in occupational sorting patterns between the healthy weight and the overweight). Additionally, as there is mounting associative evidence in the literature of relationships between occupational choice and weight gain, ignoring the possibility of this dynamic feedback mechanism (i.e. that occupations may affect body mass) would introduce bias to the estimates of how weight affects employment behavior. The data limitation is that the NLSY does not provide information on caloric intake and caloric expenditure. As such, the structural production of body mass (as a function of these inputs) cannot be modeled. Instead, the joint demands for caloric intake and expenditure are replaced by their theoretical arguments.

Thus, the parameters in the weight transition expression (equations (4.13) and (5.2)) are not themselves structural parameters but functions of structural parameters and should be interpreted as such. In other words, by controlling for environmental factors such as food prices, crime rates, and availability of exercise facilities, it is possible to control for factors that may magnify or reduce the unobservable indirect effects of employment behavior on weight via food choices. Specifically, supplying additional labor provides more money for (un)healthy food but leaves less time available for all forms of leisure, including exercise. Supplying additional labor may also encourage or necessitate agents to substitute towards restaurant meals or fast food (forsaking grocery/meal preparation time for leisure), both of which tend to be heavy in calories. During the sample period there has been a dramatic increase in the supply of "convenience food", habitual consumption of which leads to weight gain. Variation in these environmental factors and weight gain patterns informs us about how employment decisions probabilistically affect unobserved decisions regarding food and exercise.[4]

[4]Life in the United States has undergone significant change during the sample period. Fully capturing changing cultural norms about weight, the extent to which technological advancement changed life in the workplace, the appeal of sedentary leisure, changes in the supply of jobs in the varying occupations, and the amount of physical activity required in home production is beyond the scope of the model. The parameters on the variables for body mass and job requirements in the expressions for wages and fixed costs are most likely to be correlated with these factors not included in the model and therefore most susceptible to omitted variable bias or problems resulting from non-stationarity. To alleviate these sources of bias, I include the age of the agents in the specification for wages, fixed costs, and the body mass equation to capture these trends. The coefficients on the age variables then, are not directly interpretable as such.

5.5 Identification and Specification Considerations

For the identification of the model parameters, I first normalize to zero the contemporaneous utility of not working with no unearned spousal income. The vector of job requirements of not working is set equal to zero. The identification of the parameters in the contemporaneous utility function is achieved through choice frequencies, conditional on observed wages. The identification of the parameters in the fixed-cost expression comes from the frequency with which individuals at various points in the state space (and their observed wage offers) choose various occupations relative to not working. The coefficients on the job characteristics $\mathbf{J}_{jt}$ are identified by the variation in frequency of occupational choice as job requirements evolve. Note these requirements are time varying, not just occupation specific. The parameters for variable cost of working additional hours are identified by the frequency that individuals choose alternatives with part, full, or overtime hours, conditional on observed wage offers and job requirements. The exponent in the utility function is identified through changes in the response of hours worked, h_t, to variation in wages as unearned income changes. The pursuit of education early in the model also aids in the identification of the CRRA parameter as it will pick up inter-temporal elasticity of substitution with regards to consumption. If the CRRA coefficient is close to zero, the value of an additional years of education (and higher expected lifetime earnings) is greater than if the CRRA coefficient is larger.

5.6 Initial Conditions

In the model, agents are assumed to make their first schooling/employment choice at age 17. At age 17, agents are assumed to have no accrued occupational experience.[5] The endogenous state variables of years of completed schooling and initial body mass require the modeling of initial conditions. The initial condition for completed years of schooling is modeled using an ordered probit regression with birth quarter and information about presence of newspapers, magazines, and library cards as exclusion restrictions. Initial conditions for body mass are

[5]Approximately 2% of the white males in the full NLSY79 sample are married by age 17, and less than 2% of the white males in the sample has a child by age 17. All individuals in the working subsample (discussed in the data section) are single and childless at age 17.

modeled using regional dummies, information about parents' health, and the same time-varying environmental factors (linked with the geocoded data) from the weight equation. The NLSY began recording weight in 1981. However, the majority of the sample was older than 17 in 1981. I use the reported weight of the 17 year olds whose weight I do observe in 1981 to estimate the conditional distribution of body mass at age 17. For individuals whose weight at age 17 is missing, I use the aforementioned estimates and covariates to predict the distribution of missing age-17 weights. I can then combine this initial distribution and then the estimated parameters of the weight transition expression to integrate over the distribution of missing weights. Thus, I use the model to generate probabilities of an individual's weight when weights are first recorded in 1981 (Khwaja, 2010).

5.7 Solution and the Likelihood Function

In a finite horizon maximization problem, at any given time t, I model an individual's decision making behavior as if he is maximizing his expected discounted utility over the balance of his lifetime, conditional on the current state, per equation 4.14. Four factors of the model and the data must be addressed in estimation, the first of which involves the last period of the data. Modeling behavior in the terminal period of observation is essential as it serves as the anchor for solution by backward recursion. However, as discussed in section 4.8, the lives of agents continue past the horizon of the data and agents will continue to receive utility beyond the observed periods. To capture this unobserved continuation payoff, this model uses a closing function as in Mroz and Weir (2003) to approximate the unobserved future utility as a linear function of state variables including experience, body mass, and indicators for occupation in the final period. The parameters of this linear function $g(\cdot)$ are estimated jointly within the model. The final period closing function is

$$\widehat{V}(\mathbf{S}_T|\phi) = g(\mathbf{S}_T|\phi) \tag{5.3}$$

With this approximation for the closing function, the value of a specific alternative in time

$T-1$, as in equation (4.15) conditional on type and observed wage offer ω_{T-1}^{j}, is

$$V_{T-1}^{hj}(\mathbf{S}_{T-1}|\phi, \omega_{T-1}^{j}) = U_{hj}(\mathbf{S}_{T-1}, \omega_{T-1}^{j}, \phi) + \beta E\widehat{V}(\mathbf{S}_{T}|\mathbf{S}_{T-1}, \mathbf{d}_{T-1}, \phi) \tag{5.4}$$

I proceed by backward recursion to solve for value functions in preceding periods. The second factor is the size of the state space. Under ideal conditions, the *Emax* equation must be solved for all possible points in the state space. However, due to the mixed discrete/continuous nature of the state space, an *Emax* approximation is necessary. Excluding the continuous state variable for body mass, there are over 20 billion possible discrete values for the state space when agents are aged 45. Solving the model for every point in the state space would be computationally prohibitive. I therefore utilize interpolation methods as in Keane and Wolpin (1994) to approximate the *Emax* function. The goal of this method is to generate choice probabilities for each individual, in each time period, conditional on the unobserved heterogeneity and a given set of parameters. Each iteration of the solution has two stages. The first stage uses the Halton sequence draws from the state space, solving a simulated version of the model using backward recursion to attain the regression coefficients to approximate the *Emax* function. The second stage utilizes these coefficients to calculate the conditional choice probabilities, the wage density, and the BMI density.

In the first stage of model solution, starting in period T, I take 3,000 draws from the state space using Halton sequences. Each of these drawn points in the state space represents one simlated individual. For each drawn point in the state space, I construct the main equations of the model for period T, use the closing function values as the continuation payoff. I then calculate the value of being at that point in the state space, integrating out over the distribution of wages. Next, I posit a relationship between the n constructed value functions and a set of regressors. These regressors include the drawn state variables, interaction terms, and higher-order terms. I then run the regression and estimate coefficients specific to time T. I subsequently repeat the process for period $T-1$. When caluclating the epected value function in period $T-1$, I use the regresion coefficients from period T to approximate the expected future value (*Emax*) function. I repeat the process for all periods to age 17. I conduct this simulation for each age at which an individual enters the NSLY cohort (14-22), conditional on the discrete point of support of the distribution of unobserved heterogeneity, and the set of parameters, θ, currently used to solve the model. Therefore, for a given set of parameters, I conduct the simulation 9K times, where K is the number of mass points used to appoximate the distribution of unobserved heterogeneity.

In the second stage, conditional on a set of paramaters, θ and using the above regression coefficients, I solve the model for each individual. I solve the model backwards from the individual's last observed age in the model (between ages 43 and 51) to generate conditional choice probabilities, wage densities, and the BMI density. Family state transition probabilities are estimated outside the model.

The third factor which must be addresed is that individuals' wage offers in unselected occupations are unobserved when calculating conditional choice probabilities. As in Stinebrickner (2001), I integrate over the distribution of unobserved wages when calculating the conditional choice probability in equation (4.17). Defining ω_{-j} as the vector of unobserved wage offers, the choice probability conditional on state $\mathbf{S}_t$ and wage offer ω_j is:

$$P(d_t^{hj}=1|\mathbf{S}_t,\omega_t^j,\phi)=\int_{\omega_{-j}}\frac{exp(\overline{V}_{hj}(\mathbf{S}_t|\omega_j,\phi)}{\sum_{hj'}exp(\overline{V}_{hj'}(\mathbf{S}_t|\omega_{j'},\phi)}P[w_{k-1}\leq\omega_t^j<w_k|\mathbf{S}_t]\;\;d\omega_{-j} \tag{5.5}$$

which does not have a closed form solution. Integration is conducted by taking 80 Halton draws from the joint distribution of unobserved wages as estimated by CDE. Equation (5.5) can thus be rewritten as:

$$\tilde{P}(d_t^{hj}=1,\omega_t^j|\mathbf{S}_t,\phi)=\frac{1}{D}\sum_{d=1}^{D}\frac{exp(\overline{V}_{hj}(\mathbf{S}_t|\omega_t^j,\phi))}{\sum_{hj'}exp(\overline{V}_{hj'}(\mathbf{S}_t|\omega_t^{j'(d)},\phi))}P[w_{k-1}\leq\omega_t^j<w_k|\mathbf{S}_t] \tag{5.6}$$

I take expectations over the joint distribution of wages in two places in solution to the model. I take expectations over the wage distribution when calculating the value of being at a particular point in the state space in the first stage of estimation. I also take expectations over unobserved wages when calculating the conditional choice probabilities themselves.

The final factor for which I must account when constructing the likelihood function is the switching of the NLSY '79 from an annual to a biennial survey in 1994. While data on employment behavior, wages, and family status for the missing years can be recovered from the retrospective questions, I integrate over body mass in the odd numbered years. Because body mass as a state variable enters the conditional choice probabilities and transition probabilities for marriage state and number of children, integration is required when calculating these probabilities. For exposition, I define the variable y_t as follows:

$$y_t = \begin{cases} 0 & \text{if year is during annual survey period (up to 1994)} \\ 1 & \text{if year is during biennial survey period and is a survey year} \\ 2 & \text{if year is during biennial survey period and is not a survey year} \end{cases} \tag{5.7}$$

Let $G_t^{y=0}|\phi$ be the individual's likelihood contribution in period t when $y_t = 0$ and conditional on unobserved heterogeneity term ϕ, suppressing notation for $\mathbf{S}_t, \mathbf{d}_t$, and ϕ as $(\cdot)$, where

$$\begin{aligned} G_t^{y=0}|\phi = \prod_{hj=1}^{HJ} \Big[\tilde{P}(d_t^{hj} = 1, \omega_t^j|\cdot) * \prod_{l=1}^{L}(P_t^B|\cdot)^{\mathbf{1}[B_{t+1}=B_l]} \\ * \prod_{m'=0}^{3}(P_t^M|\cdot)^{\mathbf{1}[M_{t+1}=m']} * \prod_{k=0}^{1}(P_t^k|\cdot)^{\mathbf{1}[K_{t+1}=K_t+k]}\Big]^{(d_{ti}^{hj})} \end{aligned} \tag{5.8}$$

The choice probability, conditional on observed wage, is defined as above, P_t^B is the CDE weight transition probability, P_t^M and P_t^K the transition probabilities for marriage and children from equations (11) and (12) respectively. In survey years during the biennial period, the individual's contribution is similar *except* body mass transition probabilities are not calculated as body mass will not be observed in the next period. Therefore when $y_t = 1$:

$$G_t^{y=1}|\phi = \prod_{hj=1}^{HJ} \Big[\tilde{P}(d_t^{hj} = 1, \omega_t^j|\cdot) * \prod_{m'=0}^{3}(P_t^M|\cdot)^{\mathbf{1}[M_{t+1}=m']} * \prod_{k=0}^{1}(P_t^k|\cdot)^{\mathbf{1}[K_{t+1}=K_t+k]}\Big]^{(d_{ti}^{hj})} \tag{5.9}$$

and when $y_t = 2$, I use the parameters of the model to integrate over the missing body mass state variable when calculating all four probabilities.

$$
\begin{aligned}
G_t^{y=2}|\phi = \sum_{b=1}^{B} P_{t-1}^{B} \Bigg(\prod_{hj=1}^{HJ} \Big[\tilde{P}(d_t^{hj}=1, \omega_t^{j}|\cdot, B_t=b) * \prod_{l=1}^{L} (P_t^{B}|\cdot, B_t=b)^{\mathbf{1}[B_{t+1}=B_l]} \\
* \prod_{m'=0}^{3} (P_t^{M}|\cdot, B_t=b)^{\mathbf{1}[M_{t+1}=m']} * \prod_{k=0}^{1} (P_t^{k}|\cdot, B_t=b)^{\mathbf{1}[K_{t+1}=K_t+k]} \Big]^{(d_{ti}^{hj})} \Bigg) \qquad (5.10)
\end{aligned}
$$

where the cell means from the body mass CDE are indexed by b used for the discrete missing values of B_t. To complete the likelihood function I need initial conditions as discussed above. With initial condition probabilities in place, an individual's contribution to likelihood function to estimate the above, conditional on ϕ is:

$$
L_i(\Theta|\phi^k) = \prod_{t=1}^{T_i} \Bigg[\prod_{y'=0}^{2} \Big(G_t^{y'}|\phi \Big)^{\mathbf{1}[y=y']} \Bigg] \qquad (5.11)
$$

The unconditional likelihood function for an individual can then be written as

$$
L_i(\Theta) = \sum_{k} \pi_k L_i(\Theta|\phi^k) \qquad (5.12)
$$

The likelihood function is therefore:

$$
L(\Theta) = \prod_{i=1}^{N} \sum_{k} \pi_k L_i(\Theta|\phi^k) \qquad (5.13)
$$

I estimate elements of Θ with a nested pair of algorithms as in Rust (1987), but I obviously do not use a fixed point. The inner algorithm solves the dynamic model for each individual, conditional on a set of parameters and mass points of the distribution of unobserved heterogeneity. With the resulting probablities, the outer algorithm calculates the unconditional likelihood function, $L(\Theta)$, and subsequently improves the likelihood function with a BHHH gradient method. The BHHH method is commonly used for estimating dynamic structural models because it approximates the Hessian matrix of the likelihood function rather than explicitly calculating the Hessian. Explicitly calculating the Hessian would be computationally infeasible (increasing estimation time by a factor of the number of parameters in the model).

At the parameters that maximize the log-likelihood function, the average outer-product over individuals is the covariance matrix ofthe scores of the sample. At the true parameters, the covariance matrix of the scores is equal to the expected Hessian matrix multiplied by negative one. I iterate over the outer and inner algorithms until the likelihood function is maximized. I assume convergence at the maximum of the likelihood function when the percentage change of the likelihood value over an iteration is less than or equal to 0.0001. I solve and estimate the model using parallel computing (MPI) in Fortran 90.

Chapter 6

Results

This section containts the results from estimating the model. Section 6.1 contains parameter estimates for the utility function, including fixed and variable costs, wage density, body mass transition, family state transitions, and marginal effect estimates for body mass in the wage expressions. I separately report estimates of marginal effects of BMI on wages as the parameter estimates from conditional density estimation are not directly interpretable as such. Section 6.2 uses the estimated parameters and forward simulation to show how well the model fits the data.

6.1 Parameter Estimates

Tables 6.1-6.3 contain the results from the conditional density estimation of wages. Recall that CDE utilizes a logit hazard equation. A positive parameter value indicates that an increase in the variable of interest increases the probability that wages will be observed in lower quantiles of the support of wages. Conversely, a negative value indicates that an increase in the variable of interest will not be observed in a given quantile of the support of wages. Negative parameter values therefore indicate that increases in the variable of interest lead to higher expected wages. Each variable is also interacted with γ, a term that enables the effect of the variable to differ over the support of wages. Specifically, letting K equal the number of quantiles used for CDE, $\gamma = (-1) * ln(K - k)$ for each cell k in constructing the logit hazard probabilities (Gilleskie and Mroz, 2004). Because for a positive variable x, the interaction term $x * \gamma$ is negative, a positive parameter value on $x * \gamma$ indicates a positive effect on expected wages, although that effect diminishes in the upper quantiles of the support of wages. Parameter estimates for a variable x and its interaction with γ must be interpreted jointly. For example, consider the effects of a bachelor's degree on wages in Professional occupations. The estimated parameter for a bachelor's degree is -0.066, indicating that having a bachelor's degree decreases the probability that the individual's wages will fall in the lowest quantile of wages (and in the second lowest quantile, should the individual's wage not be observed in the lowest quantile, and so on). However, the estimated parameter on "bachelor's degree*γ" is 0.053. Since in the lowest quantile, $\gamma = (-1) * ln(25 - 1) = -3.17$, the combined sign on the effects of a bachelor's degree is negative (-0.066 + 0.053*-3.17 = -.225) indicating that individuals with a bachelor's degree are less likely to be observed earning wages in the lowest quantile (and each successive quantile, if calculated). This combined result indicates that the effect of the bachelor's degree on the probability that a wage is observed in a given quantile is most strongly negative in the lower parts of the distribution of wages.

Interpreting parameter results directly as marginal effects is infeasible so marginal effects of BMI and interaction effects between BMI and job requirements (and state variables) are reported in tables 6.4 and 6.5. First, per the right column in the occupation-invariant estimates in table 6.4, higher body mass is linked to lower wages in physically and socially intensive occupations, although the effect is only significant at the 10% level for the social reqirements. The relationship between body mass and wages in mentally intensive occupations is positive as a point estimate, but is statistically insignificant. In all three requirements, however, the point estimates of the interaction effect of BMI and the requirement are greatest in the upper quartile of the distribution of wages. Additionall, conditional on requirements, body mass is linked to lower wages in Sales and Administrative Occupations and Labor/Operator Occupations, with the greatest effects occurring in the upper quartile of the distribution of wages. In the case of Craftsmen and Service occupations, BMI is estimated to have a negative effect on wages in the lower quartile and inter-quartile range, but a positive effect in the upper quartile. The results are similar for laborers, but considerably smaller in magnitude. Third, higher body mass is linked to lower returns to 'white collar' experience in nearly all occupations.[1] Fourth, higher body mass reduces the return to education in white collar occupations, with the greatest effects again occurring in the top quartile.

As stated in Chapter 2, the marginal effect of body mass on wages is the estimate of the upper bound of the role of employer preferences weight-based wage differences for each occupation. While the indices of job requirements are included to capture productivity differences between individuals of different body weights, there may be productivity differences for which these indices do not account. By the same logic, I treat the marginal effects of body mass interacted with job requirements as the lower bound of the effects of productivity on weight-based wage differences. The possibility of factors such as persistence in statistical discrimination prevents me from attributing the lower returns to experience in white-collar occupations as attributable to productivity.

Tables 6.6-6.7 report the estimates for the parameters in the utility function, including fixed costs of participating in each occupation and schooling, switching costs, and variable costs. The results suggest that heavier individuals face higher fixed costs of participating in occupations with greater physical and social requirements, and lower fixed costs of participating in occupations that have greater mental requirements. Because the estimates of interaction effects of body mass and job requirements align between the wages and fixed costs, these results are consistent with the notion that employers at least view body mass as a *signal* of productivity, and that the sign and magnitude of that signal depends on what abilities the job requires.

Conditional on the requirements of the job, individuals with greater body mass are found to have lower fixed costs of working in the classes including Professionals, Technicals, and Managers (PTM) and Craftsmen; and higher fixed costs of working in Laborer and Sales/Administrative occupations. Since nearly all customer facing jobs are found in the Sales and Administrative category, this result is consistent with Hamermesh and Biddle (1994).[2] The results also suggest

[1] "White Collar" occupations include Professional, Technical, and Managerial Occupations (category 1) and Sales and Administrative Occupations (category 2).

[2] While food service workers are included in the "Service" category, the majority of individuals in the data in

Table 6.1: Estimates of Wage Density - Occupation Invariant Estimates

Variable	**Estimate**	**ASE**	**Requirement**	**Estimate**	**ASE**	**Body Mass * Requirement**	**Estimate**	**ASE**
Constant	-0.443	0.117	Physical	-0.271	0.061	Physical	0.011	0.004
γ	0.131	0.73	Physical*γ	0.023	0.034	Physical*γ	-0.007	0.005
γ^2	0.418	0.028	Mental	-0.197	0.041	Mental	-0.007	0.008
γ^3	0.179	0.005	Mental*γ	-0.130	0.013	Mental*γ	0.001	0.001
t	-0.024	-0.003	Social	-0.528	0.025	Social	0.007	0.004
t*γ	0.011	0.004	Social*γ	-0.244	0.011	Social*γ	0.000	0.002

Table 6.2: Estimates of Wage Density - Occupation Specific Variables

Occupation	Professional		Sales & Admin		Craftsmen		Laborers		Service	
Variable	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**
Constant	5.430	0.136	2.7437	0.124	2.451	0.114	0.907	0.136	–	–
γ	2.069	0.083	1.2694	0.053	0.917	0043	0.313	0.043	–	–
t	0.084	0.003	0.026	0.006	0.021	0.003	-0.068	0.005	–	–
t*γ	0.091	0.002	0.013	0.003	0.021	0.001	-0.004	0.002	–	–
Education	-0.083	0.006	-0.284	0.021	0.018	0.014	0.206	0.028	0.089	0.039
Education*γ	0.076	0.003	-0.059	0.009	0.060	0.005	0.121	0.010	0.103	0.014
Experience Occ.1	-0.086	0.003	-0.016	0.009	-0.039	0.008	0.177	0.011	0.042	0.055
Experience Occ 1*γ	0.008	0.002	0.037	0.004	0.001	0.004	0.096	0.005	0.021	0.019
Experience Occ.2	-0.216	0.005	0.036	0.009	-0.033	0.024	0.152	0.010	0.399	0.045
Experience Occ 2*γ	-0.144	0.003	0.049	0.003	-0.011	0.010	-0.047	0.003	0.210	0017
Experience Occ.3	-0.083	0.006	0.027	0.023	0.044	0.005	0.136	0.011	0.160	0.034
Experience Occ 3*γ	-0.057	0.003	0.055	0.009	0.034	0.002	0.063	0.004	0.111	0.010
Experience Occ.4	-0.101	0.008	0.088	0.018	0.023	0.009	0.122	0.007	-0.107	0.031
Experience Occ 4*γ	-0.077	0.004	0.027	0.007	0.008	0.004	0.432	0.003	-0.023	0.011
Experience Occ.5	-0.155	0.010	-0.011	0.026	-0.011	0.008	-0.132	0.017	0.217	0.010
Experience Occ 5*γ	-0.133	0.004	-0.030	0.011	-0.024	0.004	-0.085	0.006	0.106	0.004
Bachelor's Degree	-0.066	0.043	1.152	0.117	0.786	0.204	-0.717	0.382	-0.177	0.481
Bachelor's *γ	0.053	0.021	0.606	0.051	0.260	0.085	-0.291	0.137	0.035	0.179
Body Mass	0.048	0.018	0.102	0.015	-0.018	0.016	-0.020	0.019	0.084	0.034
Body Mass*γ	-0.263	0.011	-0.022	0.055	0.004	0.007	0.009	0.011	0.001	0.016

Table 6.3: Estimates of Wage Density - BMI Interacted with Experience & Education

Occupation	Professional		Sales & Admin		Craftsmen		Laborers		Service	
Variable	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**
Education	0.008	0.001	-0.003	0.013	-0.009	0.001	-0.006	0.001	-0.004	0.002
Education*γ	0.001	0.002	0.001	0.001	-0.005	0.002	-0.003	0.002	-0.003	0.001
Experience Occ.1	0.009	0.001	0.016	0.001	-0.004	0.001	-0.004	0.002	0.006	0.009
Experience Occ 1*γ	-0.001	0.000	0.002	0.001	-0.001	0.001	-0.008	0.001	0.010	0.003
Experience Occ.2	0.007	0.001	0.001	0.001	-0.002	0.002	0.047	0.001	-0.047	0.006
Experience Occ 2*γ	0.004	0.001	0.001	0.001	-0.004	0.001	0.021	0.001	-0.017	0.002
Experience Occ.3	0.005	0.001	-0.022	0.002	0.006	0.001	0.006	0.001	-0.006	0.003
Experience Occ 3*γ	0.004	0.000	-0.011	0.001	0.005	0.001	0.001	0.001	-0.007	0.001
Experience Occ.4	0.001	0.001	-0.000	0.002	0.004	0.001	0.009	0.001	-0.011	0.004
Experience Occ 4*γ	0.001	0.000	0.005	0.001	0.002	0.001	0.004	0.000	-0.002	0.002
Experience Occ.5	-0.003	-0.001	-0.003	0.003	-0.020	0.002	-0.003	0.003	-0.005	0.003
Experience Occ 5*γ	0.000	0.001	0.012	0.001	-0.005	0.001	-0.006	0.001	0.003	0.002
Bachelor's Degree	0.086	0.006	0.025	0.015	-0.018	0.016	0.312	0.045	0.020	0.112
Bachelor's *γ	0.038	0.003	0.061	0.007	0.004	0.007	0.130	0.018	-0.093	0.044
Unobserved Heterogeneity										
Factor loadings	-0.143	0.008	0.029	0.011	-.065	0.012	.017	0.013	.029	0.025

Table 6.4: Marginal Effects of Job Requirements on Wages
Occupation-Invariant Effects

Requirement	Quartile	Effect	Requirement *BMI	Quartile	Effect
Physical	Lower	0.20	Physical	Upper	-0.04
	Inter	0.37		Inter	-0.10
	Upper	0.47		Upper	-0.19
Mental	Lower	-0.28	Mental	Lower	0.03
	Inter	0.08		Inter	0.03
	Upper	0.18		Upper	0.09
Social	Lower	-0.30	Social	Lower	-0.05
	Inter	-0.09		Inter	-0.05
	Upper	1.10		Upper	-0.10

that greater body mass is linked to higher switching costs when entering white collar jobs. The effects are twice as strong for the PTM jobs than the Sales and Administrative jobs. Results therefore suggest that body mass affects occupational attainment, which in turn affects future experience and future wage distributions. This relationship is revisited in the section on simulations.

As stated above, I interpret the estimates of the variable costs as the lower bound of the effects of worker utility in creating differences in employment behavior on the basis of weight. I interpret the estimates of the switching costs as the lower bound estimate of the role of employer preferences in differences in employment behavior between individuals of different body weights. I consider both of these to be lower bounds as I cannot attribute the per-period fixed costs entirely to workers or firms, rather I treat these costs as a sort of 'tax wedge' were the share of the burden borne by workers is unknown. However, conditional on individuals receiving the wage offers they received, and any per-period fixed costs affecting individuals' selection into occupations, any differences in hours worked between individuals of different weights are the result of differences in the slope of the labor supply curve due to body weight. In the model,

"Service occupations" are not waiters/waitresses per se.

Table 6.5: Occupation-Specific Marginal Effects - BMI and Interactions

Variable	Quartile	Professional Estimate	Sales/Admin Estimate	Craftsmen Estimate	Laborers Estimate	Service Estimate
BMI	Lower	0.14	-0.18	-0.12	-0.04	-0.25
	Inter	-0.12	-0.09	-0.05	-0.06	-0.10
	Upper	-0.54	-0.25	0.39	0.07	0.15
BMI × Education (Year)	Lower	0.00	-0.01	0.02	-0.01	-0.02
	Inter	-0.02	-0.02	0.04	-0.01	-0.02
	Upper	-0.02	-0.03	0.06	0.00	-0.02
BMI × HS Degree	Lower	0.00	0.01	-0.02	0.01	0.03
	Inter	0.03	0.00	-0.01	0.04	0.00
	Upper	0.05	-0.10	-0.04	0.02	-0.03
BMI × Bachelor's Degree	Lower	0.13	-0.08	0.08	-0.49	-0.08
	Inter	-0.14	-0.13	0.08	0.10	0.01
	Upper	-0.29	-0.21	0.08	0.39	-0.11
BMI × Experience Occ.1	Lower	-0.02	-0.01	0.00	-0.01	0.00
	Inter	-0.03	-0.06	-0.01	0.01	0.02
	Upper	-0.04	-0.08	-0.02	0.00	-0.04
BMI × Experience Occ.2	Lower	0.00	0.00	-0.03	0.02	-0.03
	Inter	-0.02	-0.02	-0.03	0.04	-0.03
	Upper	-0.02	0.00	-0.03	0.02	-0.05
BMI × Experience Occ.3	Lower	0.00	0.02	0.01	0.01	-0.05
	Inter	-0.01	0.02	0.02	0.01	-0.09
	Upper	-0.02	0.02	0.00	0.00	-0.02
BMI × Experience Occ.4	Lower	0.00	0.04	0.00	0.00	-0.01
	Inter	0.00	0.05	-0.01	-0.00	-0.02
	Upper	0.00	0.06	0.00	-0.00	-0.09
BMI × Experience Occ.5	Lower	0.00	0.04	0.01	0.00	0.02
	Inter	0.00	0.13	-0.04	0.00	0.12
	Upper	0.00	0.15	-0.05	0.00	-0.06

Table 6.6: Utility Function Parameters

Variable	Estimate	ASE	Variable	Estimate	ASE
α	1.971	0.084			
Occupation-Invariant Variable Costs			Fixed Costs of Schooling		
Variable	**Estimate**	**ASE**	**Variable**	**Estimate**	**ASE**
Constant	-1.079	0.014	Constant	-2.803	0.223
M_t	-0.312	0.008	(Ed $\geq$ 12)	1.021	0.079
K_t	-0.032	0.002	(Ed $\geq$ 16)	0.869	0.142
B_t	0.003	0.001	t	0.112	0.031
hours*B_t	0.002	0.001	t^2	-0.076	0.014
Physical	-0.056	0.007	Working	1.701	0.085
Mental	-0.039	0.003	Returning	-0.277	0.024
Social	0.032	0.002			
Physical*B_t	0.002	0.001			
Mental*B_t	-0.001	0.001			
Social*B_t	0.005	0.001			
t	- 0.004	0.001			
hours*t	0.060	0.001			
hours	0.487	0.001			
Unobserved Heterogeneity					
Factor Loading	0.056	0.009	Factor Loading	-0.149	0.006

I assume that all differences in worker utility from the employment alternatives are captured by the per-period fixed costs and the variable costs of each alternative. While any additional switching costs are borne by workers, I interpret them as having origins on the unmodeled demand side of the market.

One result that is consistent with previous findings, but poses challenges for interpretation here is the exponent of the α in the utility function. Essentially, the utility function is estimated to be so concave in consumption that employment behavior is virtually unaffected by wage shocks, but entirely determined by the non-monetary costs. With these estimates, I can say something about how employment behavior affects future wages, but I can say very little about how differences in employment behavior are induced by differences in wages, nor can I assign credible wage equivalents to weight specific employment frictions. I achieved these estimates under a specification where consumption was measured in dollar units. All future extensions of this dissertation will use a specification where consumption is in \$10,000 units.

The estimates for the body mass transition equation are reported in Table 6.8. Similar

Table 6.7: Utility Function Parameters – Switching and Per-period Fixed Costs

Occupation Invariant Fixed Costs								
Requirement	**Estimate**	**ASE**	**Requirement* t**	**Estimate**	**ASE**	**Requirement* Body Mass**	**Estimate**	**ASE**
Physical	-0.084	0.008	Physical	0.003	0.000	Physical	0.005	0.001
Mental	0.002	0.003	Mental	-0.001	0.000	Mental	-0.006	0.001
Social	-0.025	0.001	Social	-0.000	0.000	Social	0.004	0.001

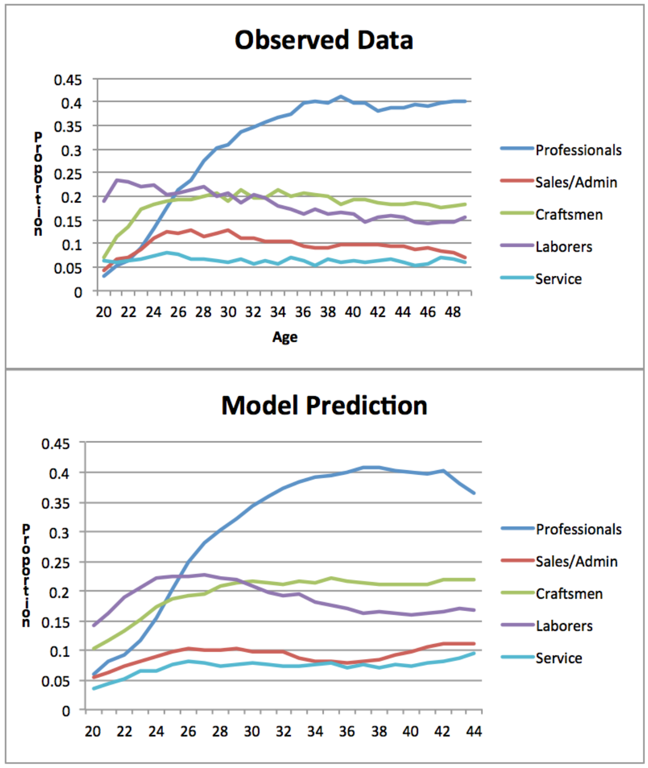
Occupation Specific Per-Period Fixed Costs										
Occupation	Professional		Sales & Admin		Craftsmen		Laborers		Service	
Variable	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**
Constant	2.594	0.129	1.562	0.056	0.950	0.036	0.609	0.047	1.992	0.392
Years of School	-0.008	0.001	-0.002	0.001	-0.015	0.001	-0.019	0.003	-0.040	0.010
(Ed $\geq$ 12)	-1.027	0.047	-0.603	0.046	-0.295	0.008	-0.465	0.051	-0.384	0.011
(Ed $\geq$ 16)	-1.553	0.041	-0.324	0.049	-0.512	0.052	0.086	0.023	0.122	0.011
Body Mass	-0.033	0.004	0.005	0.001	-0.014	0.002	0.002	0.005	0.000	0.002
t	-0.007	0.001	-0.004	0.001	0.009	0.002	0.015	0.000	0.004	0.000

Occupation Specific Swiching Costs										
Occupation	Professional		Sales & Admin		Craftsmen		Laborers		Service	
Variable	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**
$\mathbf{1}[j_{t-1} = 0]$	1.424	0.146	1.258	0.045	1.659	0.075	1.211	0.064	1.229	0.055
$\mathbf{1}[j_{t-1} = 1]$	–		0.839	0.057	1.885	0.127	1.824	0.111	0.779	0.044
$\mathbf{1}[j_{t-1} = 2]$	0.916	0.026	–		2.2336	0.045	1.563	0.072	0.918	0.091
$\mathbf{1}[j_{t-1} = 3]$	0.922	0.035	1.191	0.043	–		0.901	0.034	0.842	0.108
$\mathbf{1}[j_{t-1} = 4]$	1.744	0.068	1.212	0.026	1.371	0.062	–		0.813	0.076
$\mathbf{1}[j_{t-1} = 5]$	2.318	0.073	1.674	0.088	3.244	0.84	1.906	0.93	–	
$\mathbf{1}[j_{t-1} \neq j] * t$	0.044	0.000	0.100	0.044	0.11	0.044	0.07	0.027	0.046	0.009
$\mathbf{1}[j_{t-1} \neq j] * B_t$	0.074	0.010	0.036	0.006	-0.019	0.005	-0.000	0.001	0.000	0.004
Unobserved Heterogeneity										
Factor Loadings	-0.642	0.036	0.701	0.079	-0.941	0.081	0.059	0.016	0.863	0.057

for the results for the wage distribution, the variable γ is assigned for each cell l, equal to $(-1)ln(L-l)$, thereby permitting the effect of a covariate to vary over the support of the dependent variable. Conditional on body mass entering the period, higher wages are associated with lower body mass in the ensuing period. The wages result is consistent with the notion that higher wages garner more resources for investment in health capital (Grossman, 1972). However, the interaction effect of body mass and wages is positive. The results imply that individuals of higher body mass in period t use additional resources to further increase their body mass. The estimates for hours exhibit a similar pattern. While an increase in hours worked leads to lower body mass in the ensuing period, the interaction effect of body mass and hours is positive. The education dummies corresponding to high school and college graduation are associated with lower body mass. The estimated effect of marriage on body mass is positive; the effect of additional children on men's body mass is negative. Conditional on education, income, unobserved heterogeneity, and age; physically intensive jobs are surprisingly shown to increase body mass, whereas mentally intensive work is shown to decrease body mass. Interpreted as 'direct effects' of employment on decisions on body mass, these results are nonsensical. These results can only be explained via indirect effects, or the effects of individuals employment decisions on unobserved optimal diet and exercise behavior. Physically intensive occupations are usually not aerobic. If physically intensive work leaves the individual with less energy for more productive weight maintenance activities, the net effect of physical work on weight may be positive. Similarly, higher body mass carries greater negative consequences in white collar occupations than blue collar or service occupations. The fact that these occupations are mentally intensive may provide incentives for individuals in these occupations to invest more in maintaining a healthy weight. Future work will include specification adjustments to interact the requirements with body mass, and may model body mass maintenance as a continuous choice. This is discussed further in the conclusion.

The estimated factor loadings on the mass points of unobserved heterogeneity have the same directional effects in the wage distributions and estimates of fixed costs. Unobserved propensity to *not* gain weight is positively correlated with wages *and* reduced fixed costs in PTM occupations and Craftsmen. Unobserved propensity to not gain weight is negatively

Figure 6.1: Proportions of Occupations Chosen by Age, Model v. Data



correlated with wages and associated with higher fixed costs in Sales, Laborer, and Service occupations.

6.2 Model Fit

To assess how well the model fits the observed data, I simulate employment behavior using the model and the estimated parameters for 10,000 individuals. Initial conditions are randomly drawn using observed frequencies in the data. An individual's "type" is also drawn randomly using proportions from the estimated distribution of unobserved heterogeneity. Figure 6.1 shows the predicted proportions of chosen occupations by age and the same proportions from the observed data. The model fits the data reasonably well in terms of relative and absolute frequency, with two exceptions. First, sales and administrative work are not always chosen more often than service occupations. Second, the decrease in proportion of white males selecting work as a laborer over time is stronger in the data than in the model.

Table 6.8: Parameter Estimates for Body Mass Density

Variable	Estimate	ASE
Constant	10.407	0.319
γ	-10.252	0.100
γ^2	-0.036	0.356
γ^3	0.282	0.009
t	0.083	0.009
t*γ	0.027	0.004
$t^2/100$	-0.288	0.023
$(t^2/100)$*γ	-0.093	0.012
Body mass	-0.692	0.010
Body mass*γ	0.466	0.004
(Ed $\geq$ 12)	0.323	0.056
(Ed $\geq$ 12)*γ	0.131	0.024
(Ed $\geq$ 16)	0.458	0.074
(Ed $\geq$ 16)*γ	0.162	0.033
Married	0.144	0.057
Married*γ	0.058	0.026
hours/10	0.826	0.059
(hours/10)*γ	-0.329	0.016
hours^2/100	-0.056	0.004
(hours^2/100)*γ	-0.021	0.002
Physical	0.243	0.044
Physical*γ	0.171	0.018
Mental	-0.188	0.018
Mental*γ	-0.109	0.020
K_t	0.046	0.022
K_t*γ	-0.012	0.002
Spouse Inc. (1000's)	-0.013	0.004
Spouse Inc.*γ	-0.007	0.002
(hours/10)*B_t	0.023	0.021
(hours/10)*B_t*γ	0.319	0.055
wage	0.545	0.022
wage*γ	0.089	0.008
wage*(hours/10)	0.003	0.002
wage*(hours/10)*γ	-0.002	0.001
wage*Body mass	-0.167	0.008
wage* Body mass*γ	0.017	0.003
FF Index	0.020	0.022
FF Index*γ	0.005	0.008
Crime Index	-0.003	0.004
Crime Index*γ	0.002	0.001
Unobserved Heterogeneity		
Factor Loading	0.206	0.045

Table 6.9: Estimates for State Transitions - Marriage and No. of Children

Marriage State Transitions						
Outcome	$M_{t+1} = 1$		$M_{t+1} = 2$		$M_{t+1} = 3$	
Variable	**Estimate**	**ASE**	**Estimate**	**ASE**	**Estimate**	**ASE**
Constant	-2.824	0.064	-3.393	0.051	-4.108	0.612
K_t	0.0112	0.002	0.064	0.002	-0.161	0.002
Body Mass	0.004	0.002	0.021	0.004	-0.003	0.001
$(M_t = 1)$	5.653	0.349	3.859	0.198	2.835	0.108
$(M_t = 1) * B_t$	-0.001	0.000	0.002	0.003	-0.012	0.004
$(M_t = 2)$	4.55	0.234	6.476	0.096	4.355	0.074
$(M_t = 2) * B_t$	-0.005	0.010	-0.002	0.005	0.005	0.001
$(M_t = 3)$	4.049	0.211	4.734	0.128	6.737	0.142
$(M_t = 3) * B_t$	0.001	0.002	-0.001	0.001	0.002	0.001
Education	0.001	0.000	-0.023	0.002	0.001	0.001
Hours	-0.003	0.001	0.000	0.001	0.000	0.002
Wage	0.001	0.000	0.030	0.002	0.050	0.032

Number of children

Variable	**Estimate**	**ASE**
Constant	-1.032	0.098
K_t	0.054	0.024
Ed_t	-0.001	0.000
hours	-0.001	0.001
age	-0.071	0.008
age^2	0.000	0.002
$(M_t = 1)$	1.015	0.103
$(M_t = 2)$	0.948	0.120
$(M_t = 3)$	1.043	0.156
B_t	-0.002	0.005

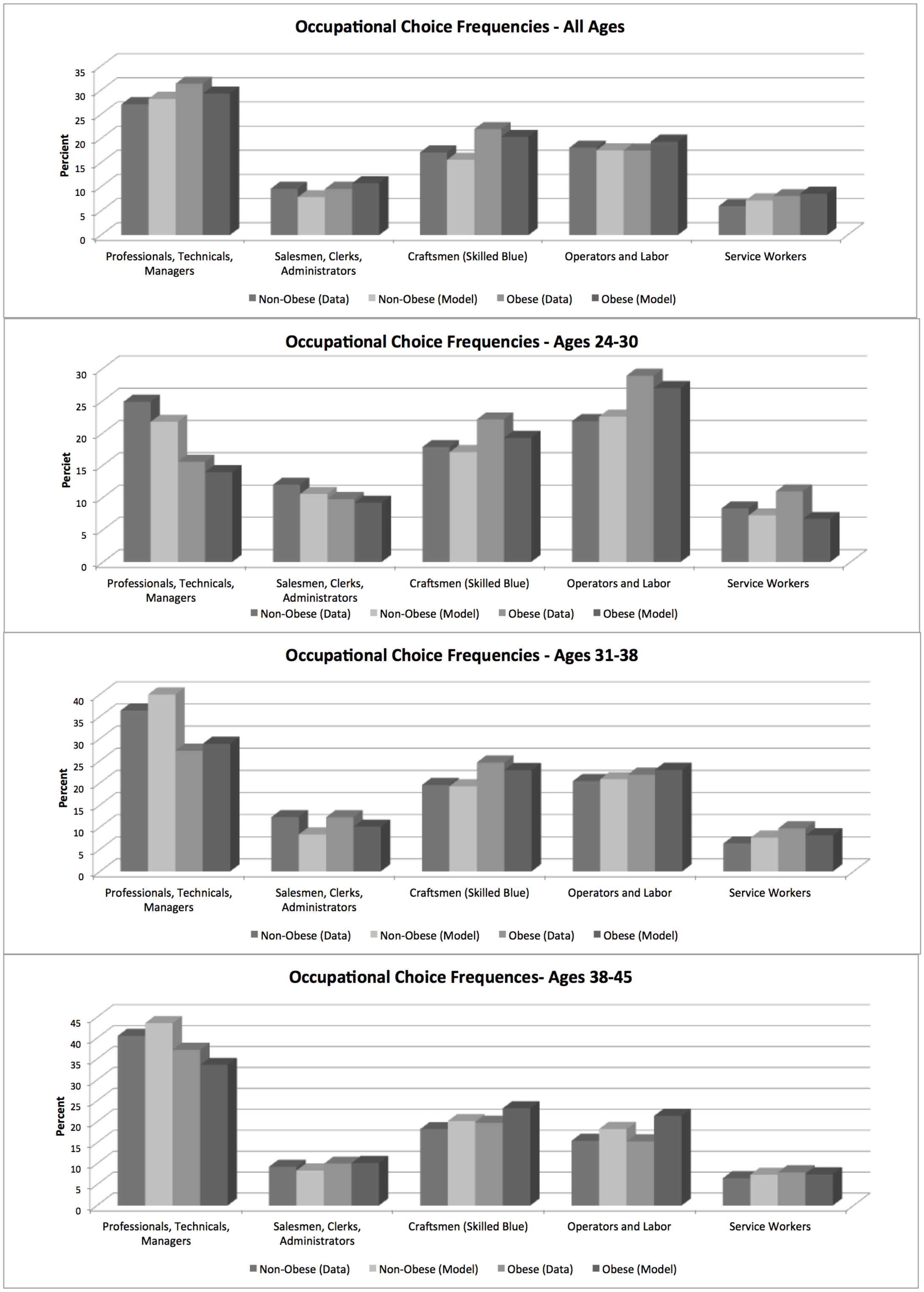
Figure 6.2 plots the observed and predicted proportions of occupations chosen for the obese and non-obese by specific age groups. The model predicts the relative differences between the obese and non-obese well. In each age group in the data, obese workers are less likely to be found in professional occupations than non-obese workers. When workers are under the age of 30, obese workers are less likely to be found in sales and administrative occupations than non-obese workers. The opposite is true in later years. The model predicts both the levels of and differences between obese and non-obese workers sorting into craftsmen, laborer, and service occupations.

Two exceptions emerge, however, that motivate a possible specification change discussed further in the conclusion. First, the model mis-predicts the dynamics of the PTM occupations with respect to body mass. In the data, the difference in proportion of obese and non-obese individuals in PTM jobs are greatest at earlier ages, converging as individuals age. Between ages 24 and 30, 24.5% of non-obese workers in the data are employed in professional occupations compared to 15.5% of obese workers, a difference of 9.3%. Between ages 38-45, 40.5% of non-obese workers in the data are employed in professional occupations compared to 37.1% of obese workers, a difference of 3.4%. The model predicts the opposite pattern, with respective values of 21.2% for non-obese workers, 13.8% for obese workers and a difference of 7.4% over the ages of 24-30. The model predicts 43.6% of non-obese workers, 33.2% of non-obese workers, and a difference of 10.4% will be found in professional occupations between the ages of 38-45.

The second key difference is that the model predicts that obese workers will consistently choose Laborer occupations in greater proportion than non-obese workers. The data show that, while this is the case in earlier ages, overall, a low proportion of obese workers relative to non-obese workers are found in Laborer occupations. This is discussed further in Chapter 8.

Figure 6.3 plots the actual and predicted wages for the obese and non-obese by age for each occupational category. In the white collar occupations where growth in wage disparity on the basis of weight is common, the model captures the growth in wages for both weight groups. In the observed data from professional occupations, obese workers make \$0.84 per hour (in 1983 dollars) less than their non-obese counterparts at age 25, and \$4.27 less than non-obese workers at age 50. The model predicts these differences to be \$1.07 and \$4.42 at ages 25 and 50

Figure 6.2: Predicted and Observed Proportions of Occ's, Obese and Non-Obese



respectively. The model also predicts the growth in the difference in mean wages as individuals age for Sales, Clerical, and Administrative Occupations. In the data, obese workers earn \$1.42 per hour less than their non-obese counterparts at age 25, and \$3.71 less at age 50. The model predicts these differences to be \$1.19 and \$3.62 respectively. As seen in Figure 6.3, the model not only predicts the end points fairly well, but also predicts the trends in between.

The model also predicts wages by weight status for blue collar occupations. Note that the scaling is smaller in the bottom three panels of Figure 6.3 as mean wages in these occupations were lower in both initial values and growth rates over the sample period. For craftsmen, the model predicts differences in wages between the obese and non-obese of \$0.17 and \$0.68 at ages 25 and 50 against respective differences of \$0.03 and \$0.50 in the data. For laborers, the model predicts differences in wages between the obese and non-obese of \$0.09 and \$1.02 at ages 25 and 50 against observed differences of \$0.16 and \$0.85 in the data. For service workers, the model captures the midcareer differences in wages between the obese and non-obese (\$0.98 predicted vs. \$0.81 in the data at age 35, and \$1.36 vs. \$1.17 age 40), but fails to capture neither the convergence of wages between the obese and non-obese, nor the negative growth in real wages in service occupations at the end of the sample period.

Tables 6.10 and 6.11 contain the observed and predicted transition matrices for obese and non-obese individuals. For non-obese individuals, the model over predicts the persistence of unemploment and under predicts the re-entry rate from unemployment into white collar occupations. The model also under predicts the switching between Operative and Craftsmen occupations by nearly 33% for non-obese individuals. For obese individuals, the model under predicts persistence of unemployment, over predicts retention in professional occupations, but under predicts switching into professional occupations. The model also over predicts transition from service work to unemployment and craftsmen to unemployment.

Figure 6.3: Predicted and Observed Differences in Wages Between the Obese and Non-Obese

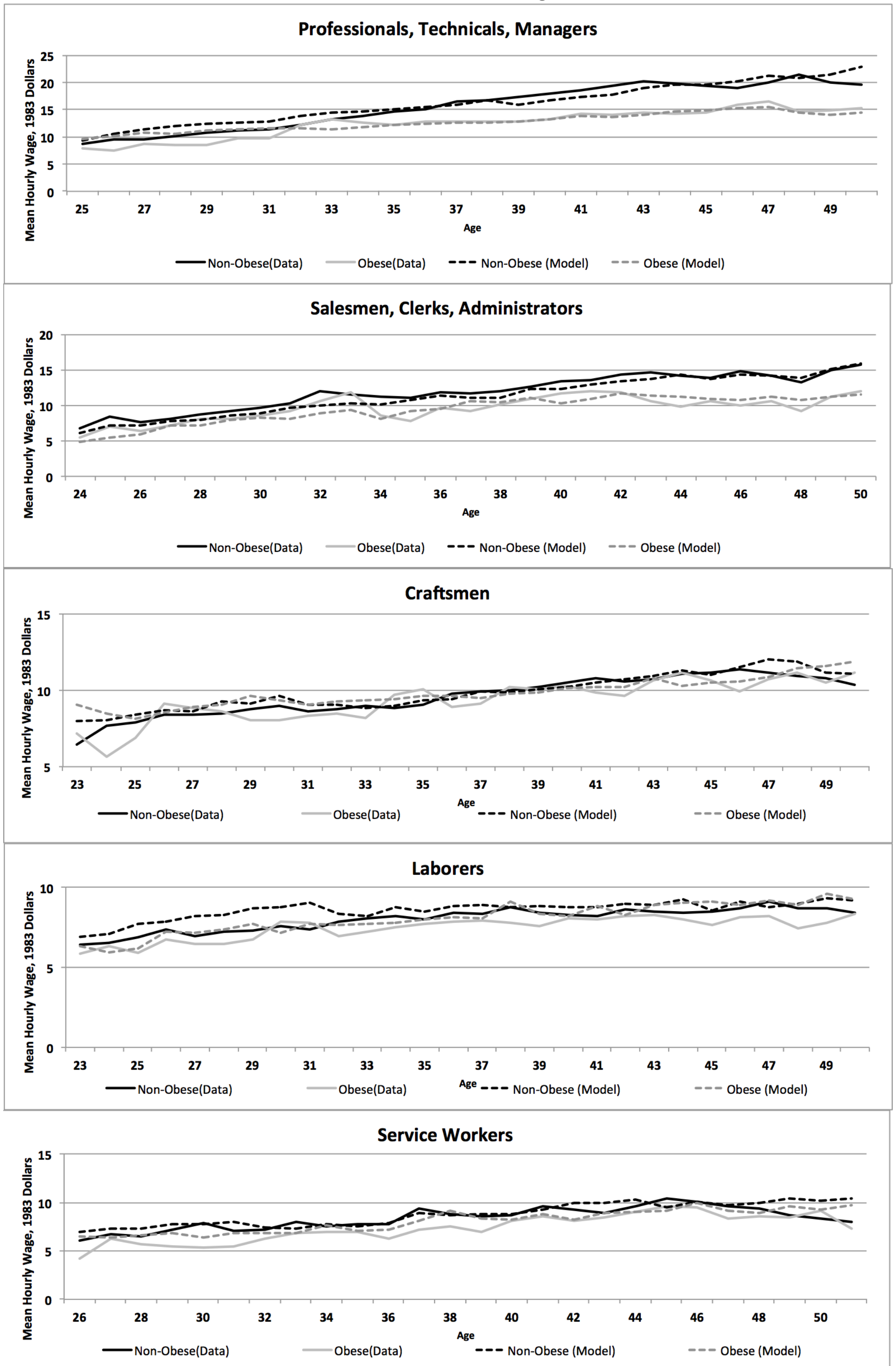


Table 6.10: Occupational Transitional Matrix - Non Obese

	$t-1$ in rows, t in columns						
	No Work	PTM	Sales/Admin	Craftsmen	Ops/Labor	Service	Total
No Work	69.55	8.81	4.11	5.22	8.58	3.72	100.00
(Model)	75.04	5.57	2.90	5.81	8.27	2.40	100.00
PTM	4.56	83.27	4.63	3.78	2.31	1.46	100.00
(Model)	3.14	84.26	2.85	3.82	2.90	43.03	100.00
Sales Admin	5.29	16.84	65.78	3.30	7.31	1.48	100.00
(Model)	6.75	14.26	65.99	3.61	5.69	3.69	100.00
Craftsmen	4.14	7.27	1.90	72.95	12.26	1.39	100.00
(Model)	5.34	7.88	2.13	72.36	9.05	3.03	100.00
Ops/Labor	6.14	4.42	4.49	12.75	68.90	3.29	100.00
(Model)	7.53	4.35	2.82	9.58	71.17	4.56	100.00
Service	8.66	7.59	2.83	5.61	10.69	64.62	100.00
(Model)	12.66	6.68	3.28	3.45	10.03	63.36	100.00
Total	20.40	28.89	9.58	17.09	18.07	5.98	100.00
(Model)	23.64	28.28	7.82	15.56	17.53	7.16	100.00

Source: NLSY '79

Table 6.11: Occupational Class Transitional Matrix - Obese

	$t-1$ **in rows,** t **in columns**						
	No Work	PTM	Sales/Admin	Craftsmen	Ops/Labor	Service	Total
No Work	67.76	11.70	3.57	5.99	6.99	3.99	100.00
(Model)	59.82	9.40	4.94	7.92	12.76	5.16	100.00
PTM	3.84	86.84	3.50	3.61	1.41	0.79	100.00
(Model)	1.76	91.13	1.34	2.22	1.62	1.94	100.00
Sales Admin	4.56	11.50	70.99	4.56	6.20	2.19	100.00
(Model)	4.62	9.95	75.10	2.33	4.92	3.08	100.00
Craftsmen	2.28	5.59	1.97	80.24	8.35	1.57	100.00
(Model)	5.06	3.51	1.81	77.24	9.28	3.10	100.00
Ops/Labor	4.44	3.06	3.45	10.26	75.64	3.16	100.00
(Model)	5.92	1.76	2.37	8.66	77.19	4.11	100.00
Service	5.75	4.20	3.10	1.77	5.97	79.20	100.00
(Model)	13.59	2.85	3.55	2.80	9.51	67.80	100.00
Total	11.61	31.34	9.56	21.92	17.49	8.06	100.00
(Model)	11.76	29.28	10.73	20.34	19.33	8.56	100.00

Source: NLSY '79

Chapter 7

Counterfactual Simulations

Having shown that the estimated model fits the observed data quite well in several dimensions, I demonstrate how this model of individual forward-looking decision making about schooling and employment (occupation and hours) as body mass evolves over time - can be used to evaluate different policy alternatives. Specifically, the estimation of policy invariant structural parameters of the individuals' optimization problem allows for introduction of policies that may not exist in the observed data. Evaluation may be based on welfare comparisons since the value of lifetime utility at time t is calculated under each scenario.

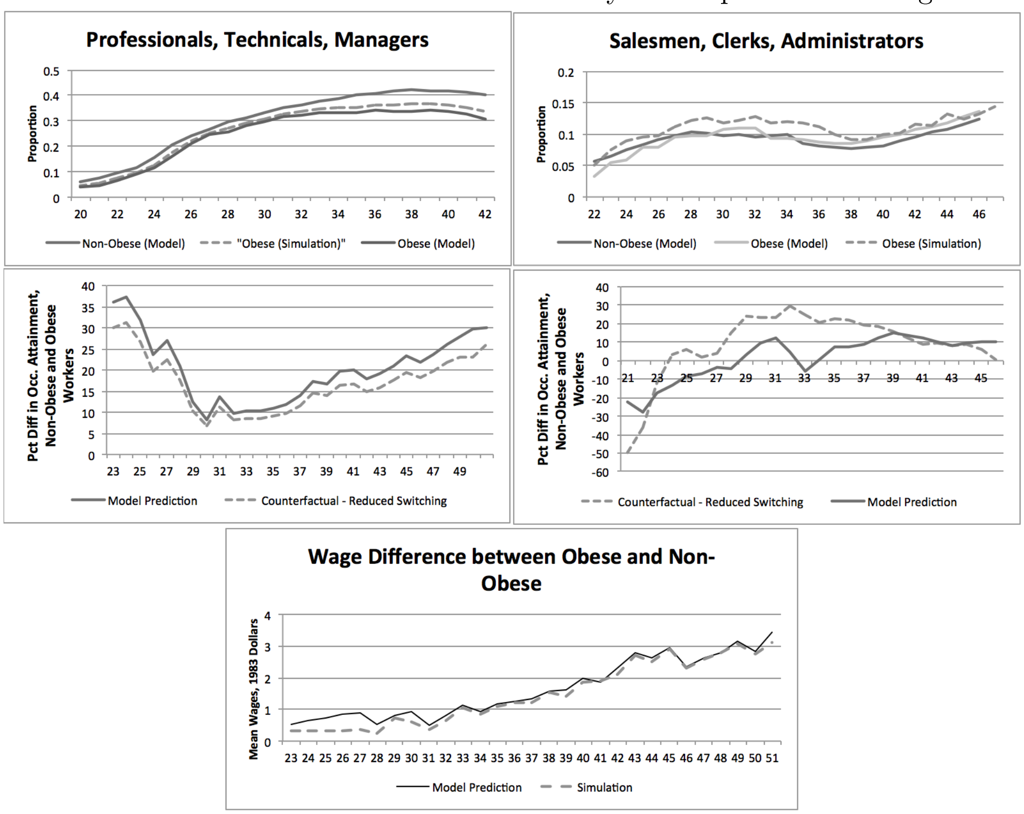
In this section, I simulate individuals' wages and employment behavior, using the specified model and estimated parameters as described in Section 2 of Chapter 6. I conduct counterfactual experiments to examine how an anti-discrimination policy that reduced weight specific labor market frictions would affect the wage and occupational profiles of obese workers. I also predict the effects of exogenous shocks to individuals initial body masses, and predict the effects of mid-career shocks to weight on individuals subsequent employment and earning decisions. Finally, I conduct simulations to evaluate what shares of the differences in wages on the basis of weight are attributable to differences in experience and education, statistical discrimination, and the estimated lower bound of employer preferences. In order to conduct these simulations, I first construct a simulated sample of 10,000 individuals that reflects the distribution of unobserved heterogeneity and initial conditions for years of schooling body mass. I then simulate wage offers, employment decisions and weight gain from age seventeen until age forty six.

The first counterfactual experiment involves a hypothetical policy that would reduce the weight specific labor demand frictions. Suppose, for example, that the Equal Employment Opportunity Commission begins levying fines against employers for discrimination against overweight workers at such a rate that employees weight specific switching costs are halved. I simulated the model under these conditions, and the results are displayed in Figure 7.1. Since the white collar occupations were the only ones estimated to have substantial entry frictions due to body mass, these occupations are the focus of this simulation. Figure 7.1 shows that such a policy would reduce the gap in attainment of Professional, Technical, and Managerial occupations by approximately 15%. The top left panel shows the predicted proportions for non-obese and obese workers as predicted by the model and obese workers as predicted by the counterfactual. The panel below converts those levels to a percentage difference. The model predicts that non-obese workers are 20% more likely to take employment in professional occupations at age 40. Under the scenario where switching costs are halved, the model predicts that figure will decrease to approximately 17%.

The upper two panels on the right side show the effects of the hypothetical policy on weight-based differences in attaining work in sales, clerical, and administrative occupations. Recall from the previous section that the model predicts (and the data show) that obese individuals are less likely to be employed in sales and administrative work in their prior to age 30, and more likely to be so employed past their mid 30's. The model predicts that halving the switching costs will greatly reduce the percentage difference between obese and non-obese workers gaining employment in these jobs in the earlier periods, and make obese workers over 20 percent more likely to work in sales and administrative occupations between the ages of 29 and 37. These occupations are high paying relative to laborer and service occupations, and for most of the sample period, have modest mental and social requirements.

The third panel in Figure 7.1 shows the growth of the difference in mean real wages between obese and non-obese workers over the sample period. The graph shows that a policy which halved switching costs attributable to body weight would reduce the difference in mean wages between the obese and non-obese by an average of 5%. Ex ante, one may expect the reduction in the wage gap to be higher, but the reduction of body-weight specific switching costs essentially eases heavier individuals transitions into occupations where they are paid less.

Figure 7.1: Counterfactual Results - Reduction of Body Mass Specific Switching Costs by Half



The second experiment I conduct examines the expected effect of an exogenous one-time mid-career shock to an individual's weight. I simulated the model as before, but reduce the individual's Body Mass Index by one weight class (5 points) at age 35.[1] The results are displayed below in Figure 7.2-7.3. Simulating the model with this shock imposed, individuals are expected to earn an additional average of \$0.87 over the next decade. This represents a 5.5% increase. This increase is driven by both a predicted increase in the proportion of workers attaining white collar worker after the shock (see left upper panels in Figure 7.2), and increases in expected wages in those occupations (upper right panels in Figure 7.2). The model predicts that such an exogenous shock would increase wages by approximately \$1.40 in professional occupations and \$.1.08 in sales and administrative occupations. The individual is 7.3% more likely to attain work in a professional occupation, and as much as 12% more likely to be employed in a sales or administrative job. This shock is not predicted to substantially affect wage offers in either blue collar or service occupational category, although the individual is slightly less likely to be employed in these categories if this shock is imposed (see Figure 7.3). Note that this experiment represents an *exogenous* shock to weight. This does not entail changing the distribution of endogeneity which affects weight and wages. Additionally, this experiment assumes the distribution of body masses in the population is held fixed. These results are valid for altering an individual within the populace rather than the whole population.

I also simulate the effects of exogenous changes in individuals' initial body mass on their wages and employment over their life course. Figure 7.4 contains the results of 2 such simulations. I decreased all individuals' body masses by 10% in one simulation, and increased all individuals' body masses by 10% in the other. The results are consistent with the predictions of the model and the previous experiment. As seen the top panels of Figure 7.4, the effects of these changes in initial body mass decrease over time as the distribution of body masses under the counterfactual converges to the original distribution. Individuals with the lowered body mass were 5% more likely to gain employment in professional occupations in their mid 20's than the original sample. Raising initial body mass had very little effect. The top right panel

[1]For a five foot eight inch male, this is the equivalent of losing 25 pounds. For a 6 foot tall Male, this equates to losing 29 pounds.

Figure 7.2: Counterfactual Results - Exogenous 5-point Loss of Body Mass at Age 35

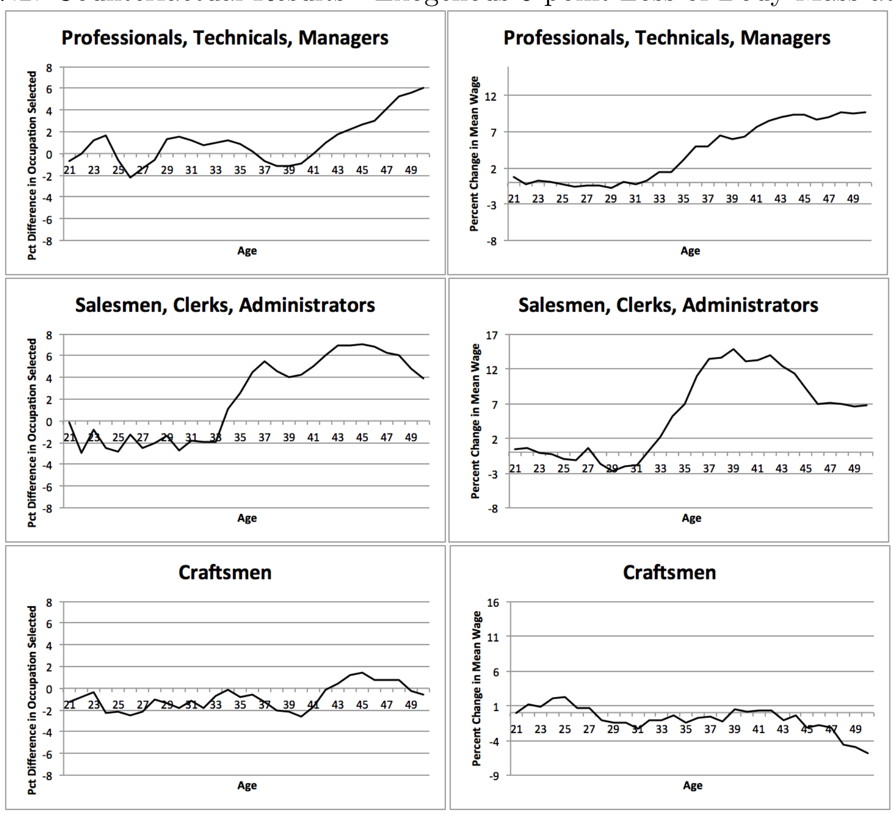


Figure 7.3: Counterfactual Results - 5-point Loss of Body Mass at Age 35 (Continued)

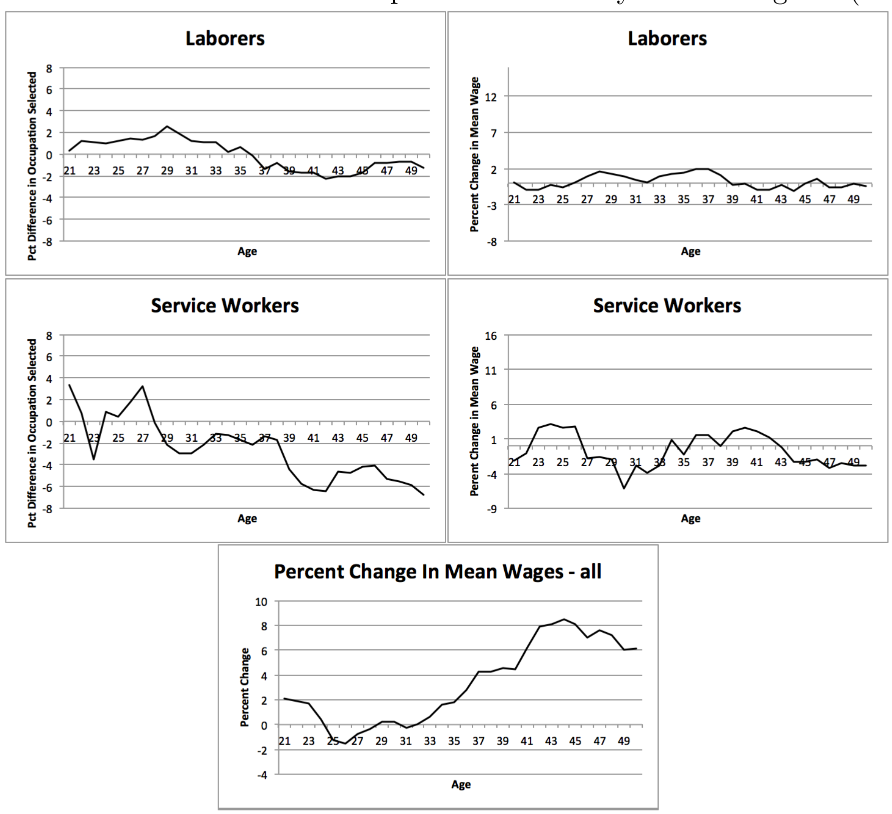
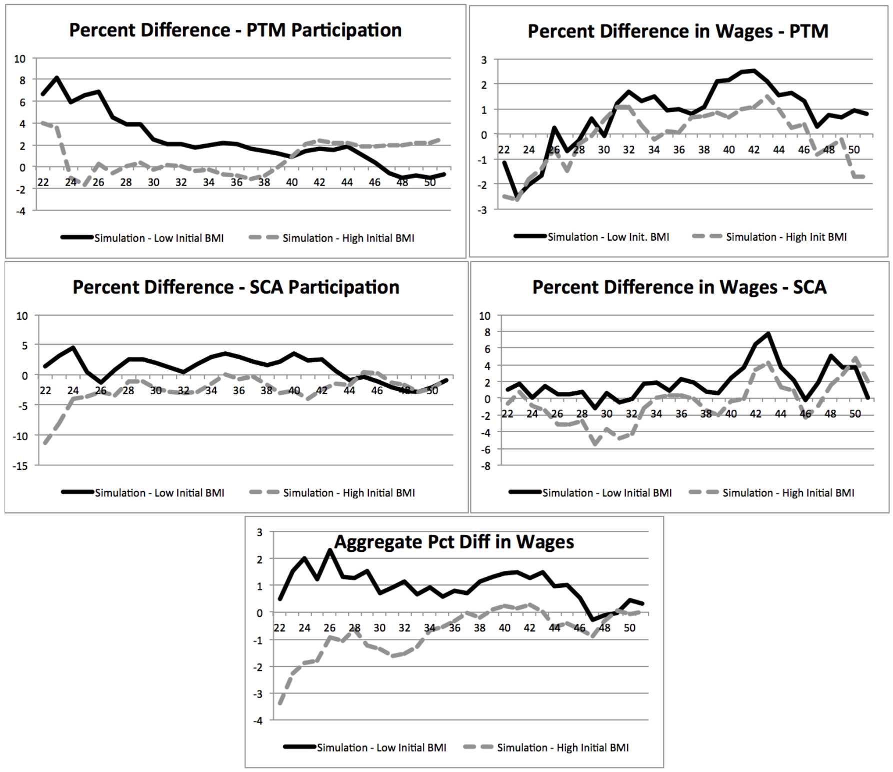


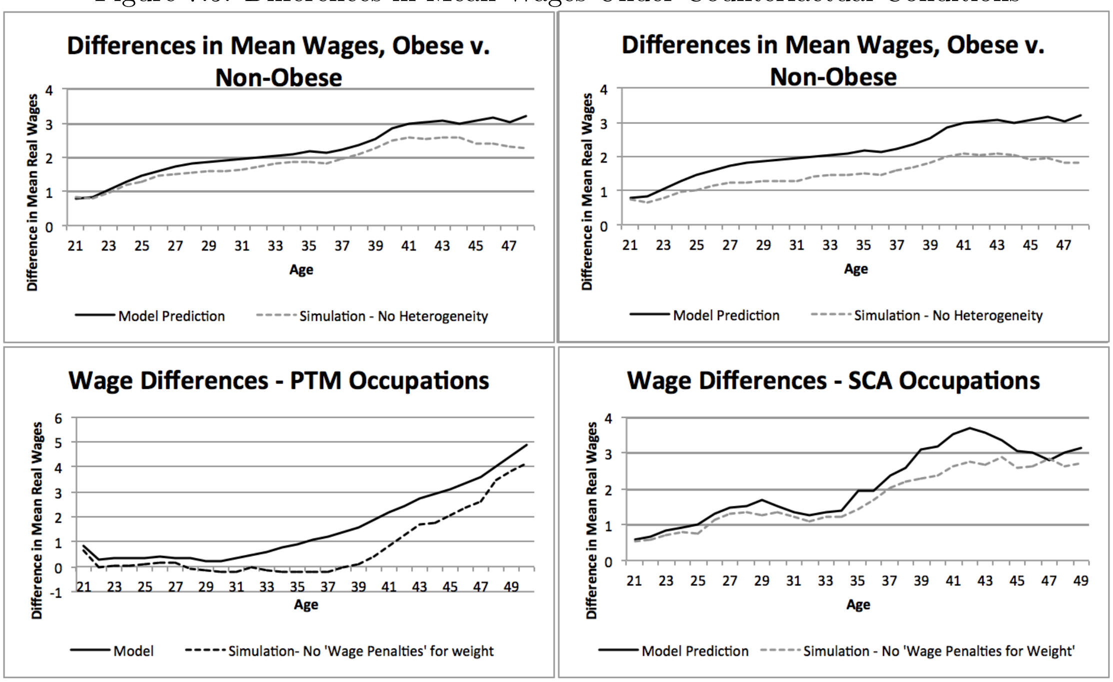
Figure 7.4: Counterfactual - Exogenous 10% Decrease and 20% Increase in Initial BMI



shows that the exogenous change in initial body weights had little effect on wages within the professional occupation over the life course. Similar effects are shown for sales and administrative occupations, although the wage result for the Sales/Administrative occuapation is very noisy. When simulating the model with lowered initial body mass, individuals are more likely to gain employment and and earn higher wages in sales and clerical occupations. The opposite effect is seen when simulating with increased initial body mass. The final panel in figure 7.4 shows that overall, a 10% increase/decrease in initial BMI leads to a 1% increase in real wages over the life course. As the effects of within-occupation wage differences are negligible, this increase is rooted in differences in occupational attainment.

Finally, I conduct simulations with certain aspects of the wage distribution held fixed to asertain what 'shares' of the observed growth in wage differences on the basis of weight are attributable to the lower bound estimate of employer preferences, changes in job requirements, and unobserved heterogeneity. Graphs of the mean difference in wages for obese and non-obese workers as predicted by the model and as predicted under counterfactual conditions are exhibited in figure 7.5. The top left panel shows that changes in job requirements account for as much as 25% of the observed growth in wages, but is only relevant in the last 10 years of the sample period. This late emergence partially due to insufficient updating in the DOT, the older of the two data sets used to caluculate job requirements. The top right panel shows that approximately 40-50% of the observed difference in wages between obese and non-obese workers is due to unobserved heterogeneity. The bottom two panels contain simulated wage differences in the two white-collar occupational categories from the model under no restrictions, and with the parameters in the wage distribution on body weight and body weight interacted with education set to zero. The results of these simulations are very different for Professional/Managerial occupations versus the Sales and Administrative occupations. In the professional occupations, restricting the wage penalty for weight to zero makes the largest impact impact when individuals are young, but that impact diminishes as the simulated sample ages. The differences in the sales and administrative occupations, grow until the last four years ofthe sample period. These results indicate that in both occupations, wage penalties for weight are a key determinant of the difference in wages, even controlling for productivity in the form of job requirements and returns to experience. In the professional occupations, however, a substantial part of the growth in observed wage differences in the basis of weight (not productivity, or unobserved heterogeneity) is due to individuals of higher body weight earning lower returns to their experience in white collar work. This supports the idea that weight may serve as a valid signal of productivity in professional and managerial occupations. To evaluate the impact of differences in experience between the weight classes, I used the estimates for the parameters of the wage distribution to evaluate the difference in wages between the obese and non-obese workers if the obese workers were arbitrarily assigned the experience profiles of non-obese workers. I found that this reduced the mean difference in wages between obese and non-obese workers by 9% and 6% for the professional and clerical occupations respectively.

Figure 7.5: Differences in Mean Wages Under Counterfactual Conditions



Chapter 8

Discussion

This study formulates and estimates a dynamic stochastic model of employment behavior and accrual of body mass. Body mass is found to lower returns to white-collar occupational experience, slightly raise returns to blue collar occupational experience, and lower the returns to education in white collar occupations. Additionally, body mass is linked to lower productivity in jobs with greater social requirements and physical requirements, and greater friction in attaining white collar occupations. While the model fits the data fairly well, the results indicate four directions for further work. First, body mass empirically enters the model as a positive difference from healthy weight, implying that the cardinal value of body mass affects wages and costs of employment alternatives. However, the distribution of body mass increases both in mean and variance as the sample cohort ages. Whereas an individual with a body mass of over 30 below the age of 25 is an outlier, an individual in the sample with a body mass index of 30 at age 50 is only slightly above average. Because the effects of body mass on the outcomes of interest are currently attributed to cardinal (rather than ordinal) values of body mass, this specification implies that the observed effects are more interpretable as productivity effects rather than signaling effects. As the model does not accurately predict the dynamic differences in sorting between the obese and non-obese, in the Professional and Labor occupations, it raises the question of whether absolute or relative body mass should affect the costs of employment. I therefore plan to examine the relationship between weight, employment behavior and wages using a relative measure of body mass in the optimization problem. Specifically, I plan to model the impact of an individual's body mass as the number of standard deviations above the time-specific cohort mean.

Second, it may be worthwhile to model weight maintenance as a continuous choice made jointly with the discrete employment choice. Modeling the utility of keeping one's weight under control will enable better estimates of welfare implications when conducting counterfactuals and more accurately capture the way employment decisions *indirectly* affects one's weight.

Third, this model was estimated using a sample of white males. Including minorities and women would be interesting but present challenges due to computational concerns and "the curse of dimensionality." However, as previous studies have found that the relationship between body weight and wages varies by gender/ethnic group, and this study shows that the relationship between weight and wages varies dynamically by occupation, perhaps the results found here (combined with gender/ethnic differences in employment behavior) can explain why the aggregate relatioship between weight and wages appears significant for some groups, but not others.

Finally, this study abstracts from choice of industry (in addition to occupation) and firm-level choices. The combination of marginal effects of weight being pronounced in the upper quartile, greater switching costs for heavier individuals into management, and lower returns to experience are consistent with heavier individuals facing tougher promotion prospects. How do those prospects vary by industry? This is an area for future inquiry.

The policy implications of his study are limited by two factors. First, these results are limited by the partial equilibrium framework - I do not have data to capture employer preferences. Any welfare implications are therefore limited to the worker and not valid at the societal level. Second, these results are valid on the distribution of body weights in the population as is, and may not be valid under conditions say, where half the population has a BMI of over 30. With that said, the results indicate that body weight limits access to certain occupations and lowers productivity where physical and social inputs are concerned. Although the simulated experiments show that the effects of weight loss dissipate over time, those are results from exogenous shocks, not persistent weight loss resulting from changes in behavior and habit. Given the implications of the study for body weight, productivity, and wage inequality, the most obvious policy implication is to raise the stakes for combatting obesity in younger adults.

Appendix A

Details on Sample and Index Construction

This appendix contains details on the construction of the data set used to estimate the model, namely particulars related to determining the years of completed schooling, correcting for errors in reported wages, re-constructing missing years in the biennial portion of the survey, reconstructing years pre-1979 for individuals aged greater than 17 at the outset of the survey, and the regression specifics for connecting job requirement indices from the DOT and O*NET.

A.1 Constructing Years of Schooling

The NLSY '79 is contains notoriously messy data on years of completed schooling. Information on individuals' education decisions are available from the following questions:

- Since the last interview, had the individual been enrolled in school full-time, part-time, or not at all? At what grade level level (e.g. High School, College, or GED)?
- Had the individual completed an additional grade since the last interview ? If so, what was the previous highest completed grade? What was the new highest grade completed?
- Has the individual attained any degrees since the last interview? If so, what is the highest degree attained by the individual?

In some circumstances, the reported data contain outcomes beyond the scope of the model. Some of these instances are due to reporting error. Examples include individuals reporting reductions in grades completed, or oscillating between grade levels, advancing grades without being enrolled in school, advancing three or more years in a single year (outside of GED completion), or failing to report changes in educational attainment until some reconciliation round. Complications also arise from non-traditional education activities including GED's, accelerated degree-completion programs, very part-time enrollment in school (e.g. one college course per year), and other educational enrollments which do not result in traditional grade advancement (certificate programs, or cosmetology school).

Because this model allows for non-linear effects of high school and bachelor's degrees on wages and non-monetary costs of employment, it is important that indicator functions in the constructed data for whether the individual has completed 12 or 16 years of schooling match whether the individual actually has earned their high school or college degree. I therefore used the following rules to determine whether an individual was enrolled in school, and if they were enrolled full or part time, conditioal on being enrolled.

- If an individual was enrolled in school in two consecutive years, and reported advancing a grade in each year, I treated that as full time enrollment in school, regardless of employment status.

- If an individual was enrolled in school in two years (consecutive or non-consecutive) and reported advancing a total of one grade, I treated that circumstance as part-time enrollment in each year.

- I disregarded GED's. A person with a 9th grade education and a GED is treated as having a ninth-grade education.

- If a person reported being enrolled in school for K years, and during that time advanced one grade level, I treated the person as being enrolled part-time (jointly with whatever employment decision they reported) for each of the last two years.

- Suppose an individual reported having completed X years of school at time t. If at some reconciliation year after t, say 1998 or 2008, the individual reported having completed $X + j$ years of school, and the individual had reported enrollment, but not advancement in the years between t and $t + j$, then I treated that as valid enrollment in school. If the individual did not have sufficient enrollement years to reconcile the difference, I treated the report in the reconciliation year as false.

- if an individual appears to have enrolled in an accelerated degree program, I credited them with full-time enrollment in school for the years in school, but I cannot match four years of completed school in two years.

- The model does not permit individuals to attend school full time and work, nor work full time and attend school. In cases where the individual reported attending school full time, working, and advancing a grade every other year, I treated that as part-time work and part-time school. If the individual reports working in excess of 35 hours per week, I recoded their hours worked to be 34 hour per week, or the highest value of hours per week classified as 'part time'.

- All years of high school education are treated as full-time school.

With these adjustments in place, I was able to reduce the percentage of mismatched observations between the indicator functions for whether the individual's constructed 'state variable' for completed years of schooling was greater than 12 (or 16), and a similar function for the individuals' self-reported highest grade completed from approximately 5% to 0.9%.

A.2 Correcting for Errors in Reported Wages

In the NLSY '79, hourly wages are a constructed variable. Individuals are asked about their rate of pay and over what unit of time (hourly, daily, weekly, bi-weekly, monthly, annually, etc.). Respondents are also asked about how many hours they work per week, the numbers of weeks worked since the last interview. Reconciling this information with reported spells of unemployment (meaning time spent not working rather than the BLS definition), the NLSY estimates the total hours worked since the last interview. Estimates of hourly rates of pay are constructed from these variables. In order to minimize the impact of misreported/misrecorded wages, I used two criteria to determine if a reported wage required further verification. First, I flagged a reported wage for further examination if an individual's wage was greater than

\$25.00 in 1983 dollars or less than minimum wage. Second, I examined the reported wage if an individual's wages increased or decreased more than 15% in a single year.

I was able to correct or verify over 90% of these flagged wages because the mistakes were obvious in the context provided by the primary variables. In most cases the fix was clear due to a decimal (wage was within a small margin of 10x times the expected amount) or a misreported pay interval (ratio of expected to reported wages was in the neighborhood of 2x, 4x, or 52/12x). In the case of some wages flagged for discontinuity (wages increased more than 15%) the change in wages was accompanied by a change in occupation. In the cases where I lacked the data to plausibly correct the reported wage, I treated the wage as missing when calculating the choice probability.

A.3 Imputing Data for Missing Years in the Biennial Phase of the NLSY '79

In 1994, the NLSY switched from interviewing respondents on an annual basis to conducting interviews biennially. However, the NLSY does contain sufficient information to re-construct the data from the non-interview years for all variables except body weight, as discussed in the section on empirical interpretation. More specifically, the NLSY asks respondents about their tenure (in weeks) at their current job; their start date at their current job; whether the respondent's current wages are the same as their initial wages; when was the current wage initiated; what was the preceding wage rate ; and start dates, ending dates, hours, wages, and tenure at up to 4 additional jobs.

I imputed occupation in the non-interview years with according to the following rules:

- If the respondent is currently employed, and has been at that job longer than 78 weeks, I assumed their occupation during the non-interview year was the same as the interview year.

- If the respondent is currently unemployed, they reported being at their last job longer than 52 weeks, and started that job within six months of the start of the calendar year of the non-interview year, I used their primary occupation for their occupation during the non-interview year.

- If the respondent has been at their current (primary) job less than 52 weeks, and started their second job within three months prior to (or six months after) of the start of the calendar year of the non-interview year, and they were at their second job for longer than 26 weeks, I used the occupation of the second job as the occupation for the non-interview year

- For any observations still missing occupations in the non-interview year, if the respondent held more than two jobs since the last interview, and their tenure at their current job is less than 78 weeks, I used the occupation with the most hours worked over the most weeks of the non-interview year as the primary occupation.

Occupation and hours were reported jointly for each 'job' held. Hours were not updated as were wages. I thusly used reported hours worked per week as paired with each occupation for each job.

I imputed wages in the non-interview years according to the following rules:

- If I coded the respondent as having any occupation other than the primary - the reported wage from that job was used.

- If the primary occupation was used, and the person reported no changes in wages since starting that job, I used the reported wage from the primary occupation.

- If the primary occupation was used, and the person reported a change in wages occurring in the last 12 months, I used the reported prior wage.

I used the age of the youngest child in the household to determine whether any child births occurred during interview or non-interview years. I also used variables on marital status, change in marital status since last interview, and date of change in marital status to impute missing information on marital status in the missing period. If there was no change in marital status over the two-year span between interviews, I used the difference in spousal income during previous-calendar-year and spousal income since-last-interview to estimate unearned (by respondent) spousal income during off years.

A.4 Imputing Data for Missing Years Pre-1979

I model individuals' joint annual choices of occupation, hours of work, and schooling from ages 17 on. However, the age of individuals in the NSLY '1979 ranges from 14-22 at the time of the initial interview. However, in that initial interview, respondents were asked about school and employment history as far back as 1974. There is sufficient information, therefore, to reconstruct employment, marriage, child acquisition, school enrollment, and wages back to age 17 for even the oldest individuals in the sample. However, as the historical data in the first round is quite messy, I used the following variables and rules to construct the individual's decision history and initial conditions.

- The initial interview contains a question "What was the last year you were in school?" All years prior to that year, I treat as years of being in school. The initial condition for years of completed schooling is then calculated by subtracting years of schooling since age 17 from reported years of completed schooling at the time of the first interview.
- If the individual reported exiting school in 1978 or earlier, and their tenure at their current job was greater than 78 weeks, I used reported occupation, hours, and wages from that job for the individual's employment decision in 1978.
- If the individual reported exiting school prior to 1978 and their tenure at the current job was less than 78 weeks, I used the longest tenured job during 1978 (the survey allowed individuals to report up to 5 jobs) for the occupation, hours, and wages data for that year.
- I followed a similar procedure for years 1974-1977.
- If any conflicting information was present about whether the individual was working or attending school, I assumed the individual was attending school.
- If at all unclear, I assumed the respondent attended school in the years they were ages 17-18.

Age of youngest child and dates of any current or previous marriage/divorces were also available in the initial round. I used these variables to construct family history back to age 17. Three people in my working sample had kids at age 17. I did not model this as an initial condition, but rather imposed that the children were born in the first year of the model, between ages 17 and 18 of the respondent.

A.5 Connecting the Indices of Job Requirements Between DOT and O*NET

As discussed briefly in the sections on data and empirical implementation, forming the time varying indices of job requirements necessitated converting the rich scaling of O*NET back to the coarser DOT data. The Dictionary of Occupational titles uses a 6-point scale for two mental aspects of a job, mathematical and language abilities. For the mental requirement of each DOT occupation (of which there are over 13,000 task level categories), I used the max value of the Math and Language Ratings. I used the social rating as given in the occupation's DOT number and the physical rating as assigned. These values fo these ratings and their definitions are listed in table 12.

The O*NET, by contrast, contains continuous 0-5 scales, interpretable as cardinal numbers for both level and importance of over 100 aspects of each occupation. To convert the O*NET ratings for each occupation to the DOT ratings for each occupation, I first multiplied level and importance for each cagetory for each occupation to get a single number for the 'intensity' of a job requrement for an occupation. I then aggregated DOT tasks and O*NET occupations (based on Census 2000) code to C70 occupation codes using BLS provided weights for the O*NET and an arithmetic mean for the DOT ratings. I then used a Welsh study from Felstead et al (2006) which studied the how occupations in the UK have changed from 1986-2006. The authors estimated percentage changes in coarse job requirements along such dimensions as literacy, mathematical skills, physical requirements. In order to connect the two indices to form a single time varying index of job requirements (for each of physical, mental, and social), a conversion of O*NET measures to DOT measures is needed. From the Felstead study, I used the skills of influence, client communication, and horizontal communication as my measures for

Table A.1: DOT Requirement Values and Definitions

Value	Interpretation
	Physical Requirements
4	Very Heavy (Exerting 100+ lbs force occasionally, 50-100 lbs frequently)
3	Heavy (Exerting 50-100 lbs force occasionally, 20-50 lbs force frequently)
2	Medium (Exerting 20-50 lbs force occasionally, 10-25 lbs force frequently)
1	Light (Exerting 10-25 lbs force occasionally, up to 10 lbs frequently)
0	Sedentary (Exerting up to 10 lbs of ofrce less than 1/3 of time)
	Mental Requirements
6	Advanced Calculus (Math)
5	Read & Write Journal level work (Language); Advanced Algebra (Math)
4	Read & Write Business level material (Language); Basic Algebra (Math)
3	Read Shop Manuals, Proper Grammar (Language); Formulaic Computational Skills (Math)
2	Literacy Rate of 190 words per minute (Language); Four-function Computation (Math)
1	Literacy Rate of 95 words per minute (Language); Addition & Subtraction (Math)
	Social Requirements
8	Mentoring
7	Negotiating
6	Instructing
5	Supervising
4	Diverting
3	Persuading
2	Speaking/Signalling
1	Serving
0	Taking Instructions/Helping

Table A.2: Occupation categories assumed fixed

Requirement	**Occupation**
	Physical Requirements
Physical	Administrative & Secretarial Occupations, Personal Service Occupations Skilled Trades (SOC 43, 33, 35 49)
Mental	Managerial Occupations, Plant Operatives, Associate Professionals (SOC 51, 11, 21, 22)
Social	Professional Occupations, Secretarial Occupatons (SOC 13, 43, 17, 19, 25)

social skills, and the aforementioned categories of interest for the mental and physical skills. Occupations which the authors treated as having an percentage change of less than 5 percent in a given requirement, I treated as being constant.

Under the assumption that the specific requirements of these occupations were changing minimally, I used regression to convert the O*NET 1998 ratings to the DOT 1991 rating scale as the requirements of these occupations did not sufficiently change. More specifically, I regressed the DOT 1991 ratings for physical, mental, and social requirements (aggregated to the Census '70) occupation code level on a set of requirements from O*NET). The results of the specifications with the highest adjusted R^2 are in Table 14.

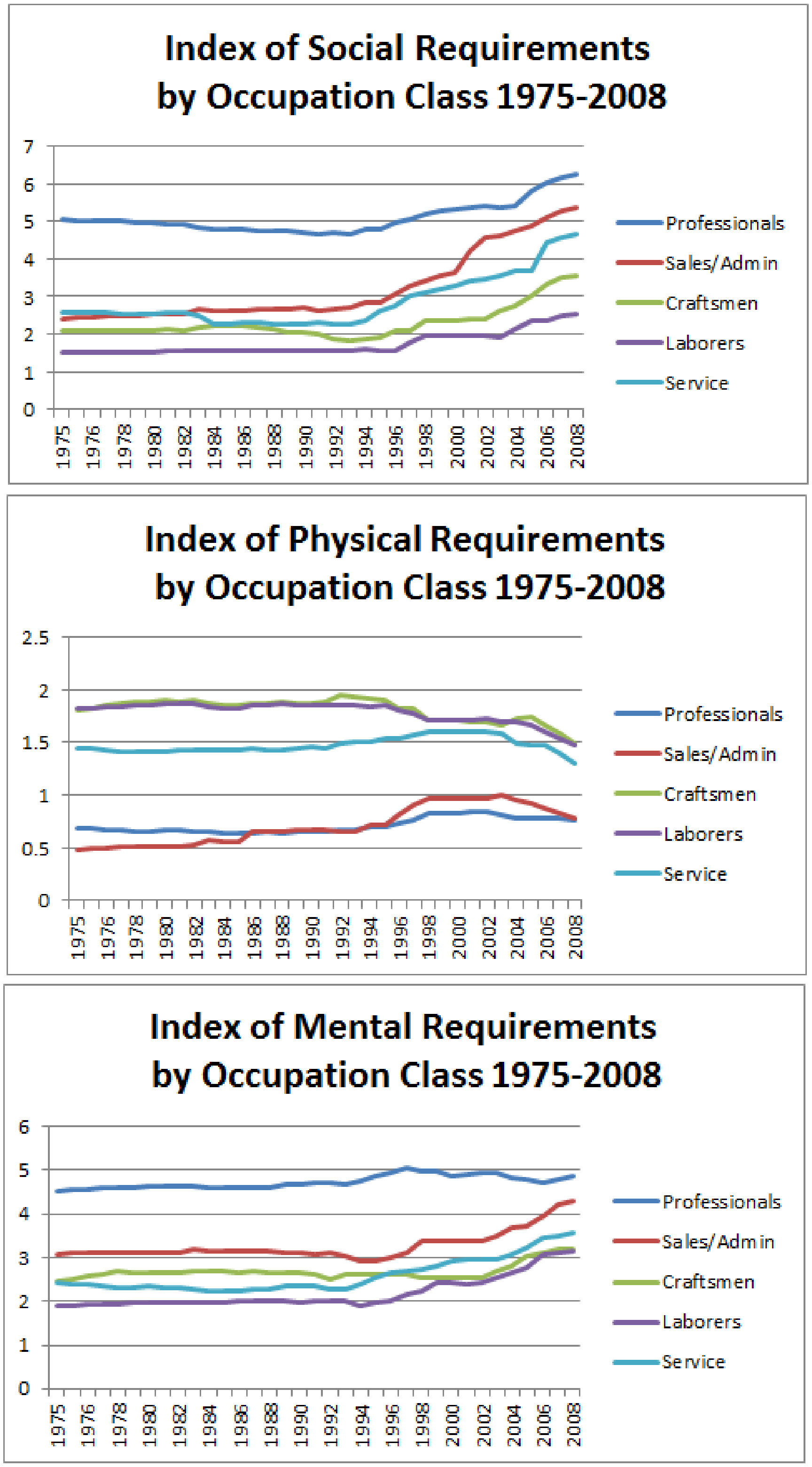
In addition to converting the rich O*NET data to single indexed values, the output of these regressions are useful in two ways. First, I can use the results from these regressions (under the assumption that the subsets of the occupations used were, in fact, unchanging in their requirements) to calculate 1998 values of requirements for all C70 occupations. I assumed that changes in job requirements are smooth and linear from 1991-1998 for the occupations not assumed unchanging for the purposes of calculation. Weighting C70 codes by their CPS weights, I calculate the requirement index values for each of the five occupational categories. Second, I can use the results from these regressions to calculate the intrinsic changes in job requirements for each Census 70 occupation after 1998. Graphs of these requirements are shown in Figure 11.

Unfortunately, all of the lines in these graphs either have a hockey-stick shape, or display more variation after the conversion to the O*NET system of rating job requirements. The primary motivation for replacing the DOT was that is was not adquately capturing changes

Table A.3: Regression Results - DOT ratings on O*NET Ratings

Variable	Estimate	Std. Err.
Physical Rating R^2=0.67		
Speed of Limb Movement	-0.004	0.016
Static Strength	*** 0.099	0.011
Explosive Strength	*** 0.055	0.018
Dynamic Strength	0.007	0.018
Trunk Strength	***-0.053	0.014
Stamina	-0.001	0.022
Gross Body Coordination	** 0.040	0.019
Constant	*** 0.957	0.055
Mental Rating R^2=0.71		
Written Comprehension	0.004	0.017
Oral Comprehension	*** 0.039	0.012
Mathematical Reasoning	-0.012	0.017
Mathematics	*** 0.036	0.014
Writing	*** 0.038	0.013
Reading Comprehension	*** 0.079	0.019
Constant	*** 1.554	0.094
Social Requirements R^2=0.66		
Active Listening	* 0.036	0.020
Monitoring	-0.028	0.019
Social Perceptiveness	*** 0.131	0.022
Persuasion	-0.004	0.040
Negotiation	** 0.063	0.031
Instructing	0.021	0.019
Service Orientation	**-0.035	0.018
Mgmt of Personnel Resource	** 0.024	0.012
Constant	*** 1.928	0.198

Figure A.1: Indices of Job Requirements by Year



in available jobs. The DOT was insufficiently agile to effectively track changes in the set of available jobs, changes in required skills for each occupation, and was a relic of a manufacturing based economy. I therefore believe if there is error in calculating changes in job requirements, it results from insufficient variation in the DOT ratings rather than excess variation in the O*NET system.

A.6 Supplementary Material on Food-Price Ratios

Per the data section, I construct an ratio of fast-food price to fresh-produce price for each city in the ACCRA data base. The summary statistics for four years spread over the sample are included listed in the table below. Unfortunately, the UNC library only has ACCRA data as far back as 1981. I used 1981 ratios for all prior years.[1].

The ACCRA data base contains data on prices of various goods in 300 cities and Metropolitan statistical areas. Approximately 71An alternative strategy of imputing missing prices would be to match the missing geographic area to the closest reported geographic area of a similar size. However, as small towns are sparse in the ACCRA dataabse, it is often infeasible to match small market or rural areas within a neighboring state area.

Table A.4: Summary Statistics - Ratio of Food Prices from ACCRA

Year	**Mean**	**S. D.**	**Min**	**Max**
1982	2.54	0.28	2.03	3.89
1991	2.86	0.27	2.18	4.38
2001	4.38	0.49	2.58	5.78
2008	4.26	0.55	3.31	5.57

[1]Adjusting for inflation is irrelevant - the ratio would remain constant under global price adjustment

Appendix B

Theoretical concerns - effects of work on weight

"In a big chunk of the literature you read out there . . . theory and data sort of get treated as substitutes" - - Anonymous Economics Philosopher

B.1 Motivation

The goal of this theoretical appendix is to show the mechanisms by which one's work decisions (occupation, on-job activity, labor supply) can affect weight status. If one's work is to affect one's weight, it should happen by affecting caloric intake or expenditure. While caloric intake is in no way observed in the data, decision rules for food and exercise choices can be formed under agent's preferences, under some reasonable assumptions. This model illustrates how even when food decisions and exercise are unobserved, when preferences are modeled and environmental factors are included as covariates, the direct and indirect effects of work on weight are captured, greatly reducing the bias from any reduced form estimate. This simple theoretic model does not include unobserved heterogeneity nor non-pecuniary rewards of specific occupations.

The agent's goal is to maximize expected lifetime discounted utility with respect to some sequence of choices over a set of alternatives. In this model, sequences of choices are made regarding occupation, denoted $\{k_t\}_{t=1}^T$ and labor supply, denoted $\{h_t\}_{t=1}^T$. The lifetime optimization problem can be formally written as:

$$max_{\{k_t,h_t\}_{t=1}^T} \sum_{t=1}^{T} \beta^t U(c_t^O, l_t, B_t; S_t) \tag{B.1}$$

where c_t^O is consumption of an aggregate good, l_t is leisure time, B_t is a measure of the agent's weight status (BMI, some non-linear measure,etc), and Ω_t is the information set (including state space) available to the agent at time t. I assume that utility is additively separable and concave in utility and leisure. Following Lakdawalla and Phillipson (2002) I assume utility of weight status takes the form of some distance function from "healthy weight," the disutility of which is monotonically increasing in distance at an increasing rate. In the standard recursive solution setting, the agent's solution to the problem in (1) can be expressed as:

$$
\begin{aligned}
V_T(S_T) &= max_{\{k_T,h_T\}} U(c_T^O, l_T, B_T; S_T) \\
V_t(S_t) &= max_{k_t,h_t} U(c_t^O, l_t, B_t; S_t) + \beta E\big[V(S_{t+1}) f(S_{t+1}|S_t, k_t, h_t)\big] \ \forall t < T
\end{aligned}
\tag{B.2}
$$

B.2 Incorporating Constraints and Laws of Motion

As written above, for the single period, the agent's single period utility is specified as follows:

$$U = U(c_t^O, l_t, B_t; S_t) \tag{B.3}$$

and is subject to the following budget and time constraints (where Ω is the time endowment)

$$
\begin{aligned}
\Omega &= h_t + l_t + ex_t \\
w_t^k h_t &= p_t^O c_t^O + p_t^F c_t^F + p_t^H c_t^H
\end{aligned}
\tag{B.4}
$$

where ex_t is the time spent exercising in period t, h_t is hours worked in period t, l_t is leisure taken in time t as shown in the time constraint equation. In the budget constraint (second line), w_t^k is the wage earned in occupation k at time t, h_t is hours worked, p_t^O and c_t^O refer to the price and consumption of the outside, aggregate good. Food enters the model in the budget constraint, where p_t^F and c_t^F are the price/consumed amount of "fattening" food and p_t^H and c_t^H are price/consumption of healthy food. Because in the data food consumption (let alone nutritional values) will not be unobserved, further assumptive restrictions are required for identification.

B.3 Reformulating the Food Problem

In the United States, food is plentiful and cheap. For the overwhelming majority of the population, eating enough is not a grave concern. Quality of food consumed, however, is concerning. To wit, one can walk into a fast food establishment or convenience store with \$1.99 and purchase over 1,000 calories of food from their value menu. While filling, this choice is highly unhealthy. Conversely, one can purchase one green bell pepper from Harris-Teeter on NC-86 for \$1.99 but only consume approximately 60 calories. Because the vast majority of Americans make over \$4.00 per day, eating enough calories is not a concern in this model.

The model assumes that every period, an agent consumes some amount of food, $F(B_t)$. $F(B_t)$ is *not* a choice per se, rather it is some hypothetical amount/poundage of food to get "full" for three meals per day and is determined solely by body weight – the size of the machine to feed.

$$\begin{aligned} F(B_t) = c_t^F + c_t^H &= (\pi_t^F + \pi_t^H) F(B_t) \quad \forall t \in \{1 \cdots T\} \\ p_t^F < p_t^H &\quad \forall t \in \{1 \cdots T\} \end{aligned} \tag{B.5}$$

The budget constraint can therefore be re-written as:

$$w_t^k h_t = p_t^O c_t^O + \pi_t^F p_t^F F(B_t) + (1 - \pi_t^F) p_t^H F(B_t) \tag{B.6}$$

Under the assumption that "fattier" food is cheaper than "healthier" food, substituting from healthy to fattening food for any given amount of total food consumed increases available resources for consumption of the aggregate good. This restriction of total food consumption to $F(B_t)$ and the simplification of food choice into "healthy" and "energy dense" also permits one key modification to the time constraint. A critical reason (if not the primary) reason that people eat out is that they do not wish to sacrifice leisure time to cooking and cleaning that is necessary for a healthy meal. In general, be it fast food, sit-down restaurant, or pre-made TV dinners - usually food that is sold as a pre-made meal is high in fat, salt, and sugar, which cause weight gain. These three ingredients are tasty, satiating, and cheap - ideal inputs for meal suppliers. Therefore it is not unreasonable to categorize pre-made meals as being subsumed into π_t^F. Preparing healthy food just takes more time - especially since recent examples of "healthy convenience" food made available the market are just that – recent. The time constraint can be transformed via the scalar K as follows to show the gain to leisure time of eating pre-made meals (which are ostensibly less healthy).

$$\begin{aligned} \Omega &= h_t + l_t + ex_t + K\pi_t^H \\ \Omega &= h_t + l_t + ex_t + K(1 - \pi_t^F) \\ \Omega &= h_t + l_t + ex_t + K - K\pi_t^F \\ \Omega - K &= \Omega' = h_t + l_t + ex_t - K\pi_t^F \\ l_t &= \Omega' - h_t - ex_t + K\pi_t^F \end{aligned} \tag{B.7}$$

B.4 The Evolution of Weight and the Role of Weight in Wages

Constrained by the restriction of some amount of food-mass $F(B_t)$, Weight (B_t) evolves as follows:

$$B_{t+1} = B_t + g(\pi_t^F, ex_t, A_t h_t) \tag{B.8}$$

where A_t is a measure of on job physical activity. The expression in (7) represents that weight is a function of calories in and calories out. Calories are expended via exercise, ex_t and physical activity performed in the workplace. Since amount of total food ingested has been restricted to some function of weight, $F(B_t)$, the primary determinant of "calories in" is the proportion of energy dense food consumed, π_t^F. The function $g(\bullet)$ is stochastic, but without a specified error.

Weight also enters the wage equation, as does prior experience, education levels and demographic shifters, etc. Suppressing all but the choice-relevant state variables for weight and accrued human capital, the budget constraint can therefore be written as:

$$w(B_t, OC_t)h_t = p_t^O c_t^O + \pi_t^F p_t^F F(B_t) + (1 - \pi_t^F)p_t^H F(B_t) \tag{B.9}$$

The term OC_t captures occupational experience. I assume occupational experience next period is monotonically increasing in hours worked. Substituting all this back into the recursive problem yields the alternative specific value function:

$$\begin{aligned}
V_t^{k,h}(OC_t, B_t) &= U(c_t^O, l_t, B_t; S_t) + \beta E\big[V(S_{t+1}) f(S_{t+1}|S_t, k_t, h_t)\big] \\
&= U(\frac{1}{p_t^O}[w(B_t, OC_t)h_t - \pi_t^F p_t^F F(B_t) \\
&- (1-\pi_t^F)p_t^H F(B_t)], \Omega - h_t - ex_t + K\pi_t^F, B_t) \\
&+ \beta E\big[V(OC_{t+1}, B_{T+1}) f(OC_{t+1}, B_{t+1}|OC_t, B_t, k_t, h_t)\big] \qquad \text{(B.10)}
\end{aligned}$$

B.5 Decision Rules and Anticipated Effects of Changes

Here, I impose the additive separability of utility in consumption, leisure, and weight. Conditional on being in an occupation k, an agent chooses to supply additional labor (h_t) up until the point where (assuming independence of OC_{t+1} and B_{t+1} conditioned on the others:

$$\begin{aligned}
U_{c_t^O}(\bullet)\frac{w(B_t, OC_t)}{p_t^O} - U_{l_t}(\bullet) &= \frac{\delta}{\delta_{h_t}}\beta E\big[V(OC_{t+1}, B_{T+1}) f(OC_{t+1}, B_{t+1}|OC_t, B_t, k_t, h_t)\big] \\
&\times (\frac{\delta f(B_{t+1}|B_t, h_t, k_t)}{\delta h_t} + \frac{\delta f(OC_{t+1}|OC_t, h_t, k_t)}{\delta h_t}) \qquad \text{(B.11)}
\end{aligned}$$

The optimal amount of labor supplied in a given occupation k is the point where the current marginal utility of consumption gained net of marginal disutility of supplying additional labor is equal to the marginal expected future discounted value of greater occupational human capital resulting from hours worked, net of any weight effects from working additional hours in that occupation. Using simple two-period notation and taking advantage of the additive separability of Utility makes it easier to expand:

$$\begin{aligned}
U_{c_t^O}(\bullet)\frac{w(B_t, OC_t)}{p_t^O} - U_{l_t}(\bullet) + \beta\Bigg[U_{c_{t+1}^O}(\bullet)\big[\frac{\delta w(B_{t+1}, OC_{t+1})}{\delta B_{t+1}}\frac{\delta B_{t+1}}{\delta h_t} \\
+ \frac{\delta w(B_{t+1}, OC_{t+1})}{\delta OC_{t+1}}\frac{\delta OC_{t+1}}{\delta h_t}\big] + U_{B_{t+1}}(\bullet)\frac{\delta B_{t+1}}{\delta h_t}\Bigg] = 0 \qquad \text{(B.12)}
\end{aligned}$$

where:
$$\frac{\delta B_{t+1}}{\delta h_t} = \frac{\delta g(\bullet)}{\delta h_t} = \frac{\delta g(\bullet)}{\delta h_t A_t} A_t + \frac{\delta g(\bullet)}{\delta ex_t}\frac{\delta ex_t^*}{\delta h_t} + \frac{\delta g(\bullet)}{\delta \pi_t^F}\frac{\delta \pi_t^{F*}}{\delta Y_t} w_t \tag{B.13}$$

where the first term refers to the change in weight with respect to on-job activity, the second refers to the change in weight with respect to exercise (and the optimal level of exercise is influenced by hours of work) and finally, the third refers to the change in weight with respect to the proportion of fatty food times the change in optimal fatty food with respect to income times the wage.

Ceteris paribus, higher activity levels at jobs should result in lower levels of weight gain over the life span. However, those results may be confounded by income effects if income and on-job activity are negatively correlated. If an additional hour of work affects neither weight nor wages in the future, the problem is essentially a repeated static optimization subject to preference shocks. To further analyze (12), decision rules are needed for π_t^{F*} and ex_t^*.

B.6 Decision Rules for Unobserved Food Consumption and Exercise

Following the same rationale and two-period simplification as above, individuals will consume proportions of energy dense food so that:

$$\begin{aligned} U_{c_t^O}(\bullet)\frac{(p_t^H - p_t^F)}{p_t^O}F(B_t) + U_{l_t}(\bullet)K + \beta\Bigg[U_{c_{t+1}^O}(\bullet)\big[\frac{\delta w(B_{t+1}, OC_{t+1})}{\delta B_{t+1}} \\ - (\pi_{t+1}^F p_{t+1}^F + (1-\pi_{t+1}^F)p_{t+1}^H)\frac{\delta F(B_{t+1})}{\delta B_{t+1}}\big]\frac{\delta g(\bullet)}{\delta \pi_t^F} + U_{B_{t+1}}\frac{\delta g(\bullet)}{\delta \pi_t^F}\Bigg] = 0 \end{aligned} \tag{B.14}$$

Similarly, for a given choice of occupation and hours, individuals will exercise until the point where:

$$\begin{aligned} U_{l_t}(\bullet) = \beta\Bigg[U_{c_{t+1}^O}(\bullet)\big[\frac{\delta w(B_{t+1}, OC_{t+1})}{\delta B_{t+1}}\frac{\delta g(\bullet)}{\delta ex_t} - (\pi_{t+1}^F p_{t+1}^F + (1-\pi_{t+1}^F)p_{t+1}^H)\frac{\delta F(B_{t+1})}{\delta B_{t+1}}\big] \\ \cdot\frac{\delta g(\bullet)}{\delta ex_t} + U_{B_{t+1}}\frac{\delta g(\bullet)}{\delta ex_t}\Bigg] \end{aligned} \tag{B.15}$$

Without modelling preferences over types of food or incorporating any rational addiction, this model does capture the inertia often observed regarding healthy/unhealthy lifestyles. An increase in the proportion of fattening food this period leads to an increase in the body mass of the individual next period, which in turn increases the amount of food needed to satiate the individual, $F(B_{t+1)}$. The increase in the amount of food required raises the total amount spent on food in period $t + 1$, leaving less income for consumption, *unless* the individual increases the proportion of unhealthy food even further. An increase in exercise in period t will have the opposite effect, lowering the body mass next period, and reducing the cost of proportional substitution to healthy food. However, the weight accrual process is stabilized by the direct utility from weight status. At some point, the direct utility from weight status wil be one of two things: either large and sufficiently negative as to cause the individual to make lifestyle changes, or become negligible as ideal weight is met, thereby decreasing the optimal proportions of health food and exercise. There are some people who take things to extremes and become triathletes or shut-ins. While this model will not capture those extreme behaviors, it should serve reasonably well for modeling the behavior for the vast majority of the population.

B.7 Comparative Statics of Optimal Food/Exercise Decisions

With these decision rules laid out, we can now discuss some comparative statics for these decision rules. As the price ratio of healthy food to energy dense food increases, the optimal proportion of fattening food consumed increases and next-period weight increases. The notion of price is not restricted to the monetary price of the two food categories. As discussed in the time constraint, these two food groups often have very different time requirements for their consumption. The time cost of picking up a hamburger at a fast-food establishment is considerably lower than that of preparing a healthy meal. Therefore it follows that as supply-related factors of the food market change over time, (e.g. as fast food and full service restaurants proliferate) optimal feeding patterns should change.[1]

[1] While the idea of "healthy-convenience" food has seen a boom recently - a.) it's less healthy than one is usually led to believe, and b.) such options are only readily available in the last few years of data. Any confounding factors attributable here should be minimal

Exercise is similarly affected by supply side and environmental factors.[2] Increases in exercise facilities available in the area should lower the time cost of burning calories outside of work, ceteris paribus.

Finally, for a given level of labor supply, h_t, and vector of prices, lower wages should result in a higher proportion of energy dense food consumed. Consider an agent operating at their optimal π_t^F so that equation (13) holds. If wages fall, then with food behavior fixed ex-ante, consumption of the outside good falls, $U_{c_t^O}$ rises (due to concavity of utility assumption) and the left-hand side is now greater than the right. Increasing π_t^F will lower the value of the left hand side. On the right hand side, the positive change in π_t^F will increase the marginal utility of consumption (via consumption reduction) through both the wage penalty and the increase in total required food, $F(B_{t+1}$. The direct utility term for weight in period $t + 1$ determines to what extent someone substitutes into energy dense food from a decrease in wages.

B.8 Mapping Decision Rules to the Empirical Specifications

This paper models two things: the effects of one's weight on work choices and the effects of one's work decisions on one's weight. The effect of one's weight on work decisions are clearly delineated in the empirical specification. It is clear how, when, and if effects of weight on wages or non-pecuniary utility of occupational choice or disutility of working will manifest. However, with the theory imposed on the individual's optimization problem, the effects of work decisions on weight are more apparent. Recalling equation (12), it should be farily clear that a decrease in on-job activity will, ceteris paribus, weakly increase the weight of the individual in the next period. I qualify the increase with "weakly" because it is unclear to what extent the optimal amount of exercise (as determined by (15)) will compensate. In real life, preference for physical activity is a critical determinant of that change in exercise level. In this model where that cannot be observed, the optimal response depends on preferences for sedentary leisure, wage penalties, disutility of being overweight, and the relative strength of response of weight to on-job activity/exercise.

[2] I completely disregard the engodeneity of the environment in this model.

We can now speculate about the sign of $\frac{\delta B_{t+1}}{\delta h_t}$ in equation (13). To the extent that the job is sedentary, the first term will be positive. By the assumption that utility is concave in leisure, $\frac{\delta ex_t}{\delta h_t}$ is weakly negative. For the sign of the third term, $\frac{\delta \pi_t^{F*}}{\delta h_t}$, the implicit function theorem is necessary:

$$\frac{\delta \pi_t^{F*}}{\delta h_t} = -\frac{U_{c_t^O}(\bullet)\frac{w_t}{p_t^O} - U_{l_t}(\bullet) + \beta\Big[U_{c_{t+1}^O}(\bullet)\big[\frac{\delta w_{t+1}}{\delta B_{t+1}}\frac{\delta g(\bullet)}{\delta h_t} + \frac{\delta w_{t+1}}{\delta OC_{t+1}}\frac{\delta OC_{t+1}}{\delta h_t}\big] + U_{B_{t+1}}(\bullet)\frac{\delta g(\bullet)}{\delta h_t}\Big]}{U_{c_t^O}\frac{(p_t^H - p_t^F)}{p_t^O}F(B_t) + U_{l_t}K + \beta\Big[U_{c_{t+1}^O}\big[\frac{\delta w_{t+1}}{\delta B_{t+1}} - E(\overline{p(F_{t+1})})\frac{\delta F(B_{t+1})}{\delta B_{t+1}}\big]\frac{\delta g(\bullet)}{\delta \pi_t^F} + U_{B_{t+1}}\frac{\delta g(\bullet)}{\delta \pi_t^F}\Big]} \tag{B.16}$$

where the expression $\frac{\delta g(\bullet)}{\delta h_t}$ can be decomposed into three separate components as in (13). As is, the sign of the expression is indeterminate, but a function of the wages, current amount of leisure, price spread between healthy and unhealthy food, etc. The denominator is almost certainly positive unless the wage penalties from weight are *very* strong or the individual's current weight status is such that the disutility from weight gain is very high. Assuming that the denominator is in fact positive, the whole expression is more likely to be positive if the marginal utility of leisure term in the numerator dominates.

The implications of this result seem consistent and reasonable. Greater differences in price between healthy and unhealthy food will result in a larger increase in unhealthy food consumed resulting from an increase in labor supply. Higher wages will result in a smaller increase in π_t^F. Having less leisure time at the outset will result in larger increases in optimal π_t^F in response to an increase in hours worked.

With the expression in (16) we can now reexamine the relationship between hours and weight in equation (13). Having discussed that the change in optimal exercise amount in response to a change in labor is weakly negative, it is now apparent how one's work choices affect one's weight both directly and indirectly. Longer work hours in sedentary jobs with low wages are most likely to lead to weight gain through direct and indirect effects.

B.9 Summary

A similar expression to (16) for $\frac{\delta ex_t^*}{\delta h_t}$ can be easily composed. Although food and consumption are not included in the data, I do have data on food price indexes, aggregate prices, hours of work and family info (to approximate leisure) and supply side variables for pre-made meals to approximate the convenience factor of unhealthy food, K. Because this is a structural model which models preferences for consumption, leisure and body weight, all the preference terms in equation (16) are included in the model and will be included into the agent's decision making.

Hopefully, this serves to strengthen the argument that work decisions to lead to weight gain and can be captured in a structural framework despite not being able to observe food and exercise.

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